New facts for old debates: Farm size and productivity in US agriculture

Temel, Tugrul

Development Research Institute (IVO), Tilburg University

29. June 2011

New Facts for Old Debates: Farm Size and Productivity in US Agriculture

Tugrul Temel
Development Research Institute
Tilburg University, Tilburg, The Netherlands
t.temel@uvt.nl

June 28, 2011

Abstract

This study examines the relationship between farm size and productivity in U.S. agriculture during 1982-92. A nonparametric regression method is applied to detect ex-post geographical patterns in changes in farm size and productivity. The estimations show that (i) in 1982 productivity per acre was high in the East, West, and South, modest in the middle part of the U.S., and low in the North, and this pattern remained the same during 1987-92, while the level of productivity continously increased over time; (ii) during 1982-92 farm size remained unchanged, large farms in the middle belt stretching from North to South and small ones in the East, West and South; and finally (iii) during 1982-92 an inverse relationship grew stronger between farm size and productivity. Furthermore, with the application of Markov chains approach, we projected the above patterns into the future. The findings suggest: (i) farms are likely to experience lower productivity; (ii) small and large farms are likely to coexist as medium-sized farms to vanish; and (iii) the inverse relationship is likely to show a strong geographical pattern.

JEL Codes: Q01, Q12, Q15, Q18, C14, R14

Key words: Farm size, productivity, geography, inverse relationship, U.S. agriculture, nonparametric regression, Markov chains.

1. Introduction[1]

How large are the largest farms relative to the smallest? How might farm size look like in the future? Are small farms more productive than large ones? If so, are large farms becoming smaller? These questions have been the subject of much theoretical and empirical work over the last two decades.[2] In recent years, however, size and productivity issues have received renewed interest in the context of U.S. agriculture because of several alarming structural changes that occurred during 1959-1992.[3] First, farm size showed a tremendous increase. Average acreage per farm increased by 62 percent due to 48 percent decline in the number of farms, and in nominal terms average farm sales per farm increased tenfold. Second, the distribution of farms changed following price changes, technological advances, and changes in labor/capital mix. More recently, during 1978-1992, the total number of farms decreased by 15 percent, and farms with sales under $100,000 accounted for the entire decrease, while the number of farms and the share of farms with sales of $100,000 or more increased. Third, noncommercial farms made up the bulk of farms (almost 75 percent), but commercial farms produced most (91 percent) of the Nation's agricultural output. On average, commercial farms had sales 28 times as high as noncommercial farms and acreage 5 times as great.

These changes entail several implications for people not only employed in agriculture but also in related sectors. The first relates to low incomes in rural areas and a desire to insure some minimum level of living for farmers and their families. Falling agricultural incomes, together with emerging biotechnologies, have rekindled concern over farm structure and the viability of the family farms. During the period of 1982-1997, for example, average farm size in the U.S. has grown considerably, with 22 percent increase in per farm crop land due mostly to the decrease in the number of family farms (USDA, 1992). The second reason relates to efficiency and business management issues, such as finding the least-cost bundle of

[1]The authors would like to thank Kim Nielsen and Judith Sommer of USDA/ERS for providing us farm price data and some publications on the U.S. farm structure, respectively.

[2]A voluminous literature exists on the size -productivity relationship. Among others, see Harris and Nehring (1976), Gardner and Robe (1978), Stanton (1978), Cornia (1985), Binswanger and Rosenzweig (1986), Fawson and Shumway (1988), Chavas and Cox (1988), Cox and Chavas (1990), de Janvry, Fafchaamps, and Sadoulet (1991), Barrett (1993), Evenson and Huffman (1997), and Peterson (1997).

[3]For a detailed discussion of changing characteristics of U.S. farms, the reader is referred to Hoppe, Green, Banker, Kalbacher, and Bentley (1993), Sommer, Hoppe, Green, and Korb (1995), and Dismukes, Harwood, and Bentley (1997).

resources, finding combinations of resources which are productive and discovering ways to combine them successfully on individual farms. The third reason concerns distribution of land and agricultural resources amongst farmers and others.

The present study evolves in two steps. In the first step, we analyze changes likely to occur in farm size and farm productivity in U.S. agriculture. More specifically, we are interested in whether or not farm size and productivity shows convergence in the sense that geographical divisions and regions all experience the same farm size and same productivity.[4] In the second stage, we examine the past and possible future relationship between size and productivity. The literature is rich, providing evidence that small farms are more productive than large ones;[5] however, it is poor in projecting the long run inverse relationship (IR) between size and productivity, although the IR is closely related to problems of agricultural stagnation, poverty, natural resource degradation, and migration. In the context of U.S. agriculture, the IR constitutes a core argument for efficient management of natural resources and for policy design to remedy imperfections in agriculture and agriculture-related markets. Labor-extensive farming on big holdings generates a class of marginalized landless laborers unable to obtain land or employment in the fertile agricultural areas. This excessive labor is driven to cultivate ill-suited tracts in forests, uplands, steep hill-slopes and arid lands (Repetto and Holmes, 1983), causing devastating ecological consequences, such as deforestation, loss of wildlife habitual, soil erosion and so forth. On the other hand, in the context of agrarian economies, the IR constitutes a core argument for redistributive land reform as it implies that land reforms which lead to a more equal size distribution of holdings, by improving both efficiency and equity, will promote rural growth and poverty alleviation (Eckstein, et al., 1978; Lipton, 1993).

In the literature, the often observed IR is usually examined at the aggregate

[4]Convergence in size and productivity is an intrinsic element of the profit-maximizing agents paradigm. Consider, for example, farm production function, $Y = AF(L, N)$, where Y, L, and N denote agricultural production, land, and the number of farms in a county, respectively. The term A reflects the state of technology. Rewriting it in terms of labor yields $y = Af(l, 1) \equiv Af(l)$, where y and l stands for output and land per farm. As a result, convergence of y is immediate from the convergence of l. Convergence is conditional upon the application of a constant returns to scale technology, the presence of competitive agricultural markets, and the absence of production externalities. What should also be noted in the above formulation of agricultural production is that convergence would further imply that l and y are cointegrated, and hence suggesting that there is a long run relationship between l and y.

[5]For example, Feder (1985), Biswanger and Rosenzweig (1986), Eswaran and Kotwal (1986), de Janvry (1987), and Taslim (1989) point out supervision costs as a potential source of the IR between size and productivty.

level that gives minimal consideration to location-specific factors, and therefore ignoring geographical peculiarity of the size-productivity relationship. To the best of our knowledge, what remains uncovered in the literature is whether or not convergence and/or the IR reveals spatial patterns. With a geographical orientation, this study implicitly assumes that location-specific changes in policy or economic environment are contagious. The present study aims at examining farm size, productivity, and the IR between size and productivity in U.S. agriculture over the period 1982-1992. The examination is carried out at the divisional, regional, and national levels. A nonparametric regression method is applied to detect geographical patterns in changes in size and productivity, and Markov chains method to project the ex post patterns into the future. This is the major contribution to the literature.

The nonparametric regression method, adopted from Hardle (1990) and Keyzer and Sonneveld (1997), allows to test for several hypotheses which are less dependent on parametric specification. This regression further reduces the influence of outliers in the sample by assigning small likelihood of occurrence to them. With its measurement error structure in independent variables, the regression is more realistic as the data used in this study are survey data which are highly likely to contain measurement errors. Of course, this regression has several shortcomings to be mentioned.[6] Among most commonly known is the curse of dimensionality expressed as the inverse relation of the speed of convergence with the number of independent variables. A second commonly cited is the selection of a smoothing parameter, especially when there are numerous explanatory variables. A third shortcoming is that nonparametric estimations require larger data sets than do parametric estimations in order to achieve the same rate of convergence, and therefore parametric methods would be desirable when the data set at hand is small.

Markov chains, adopted from Quah (1993, 1996), are applied to characterize the long run tendencies in size and productivity.[7] This method projects the current distribution forward and derives the time-invariant distribution of the variable of interest, enabling the detection of regularities that intra-distribution dynamics contain. Specifically, it allows analysis of how the top, say, 5 percent of the distribution behaves relative to the bottom 5 percent, and of long run projections

[6] The reader is referred to Yatchew (1998) for a recent survey of nonparametric regression techniques.

[7] For applications of Markov chains to analyze farm size distribution, see Garcia, Offutt, and Sonka (1987) and Edwards, Smith, and Patterson (1985).

of cross-movements of observations in the top and bottom parts of the distribution as the forecast horizon grows. Having knowledge of the shape and stability of the long run distribution should provide insights into the characteristics of an average farm. Although Markov chains provide useful representation of dynamic processes, they also have several pitfalls. Perhaps the most important one is that they cannot answer the question of why changes take place over time. The second is that stratification of the observations becomes demanding when there is more than one stratification variable. The third is that Markov chains assume no measurement error, while in many economic variables errors of some kind are unavoidable. Nevertheless, we apply the nonparametric regression and the Markov chain techniques since they provide insights into size and productivity issues that our study addresses.

This study should provide policy makers and academicians with information and decision aids as to farm productivity and (dis)economies of size. Anticipation of future changes in farming is vital as the potential social and economic gains and losses are high from anticipating and recognizing major structural changes when they occur. Hence, some kind of limits to farm size has always been a core issue in policy design that aims at promoting farms large enough to compete successfully in a commercial environment. Furthermore, size and productivity issues have for decades remained on the agenda of academicians as characteristics of production technologies are of a vital importance in economy wide modeling.

The rest of the study is organized as follows. Section 2 describes the nonparametric regression and Markov chains techniques. Data, variables, and geographical groupings of counties are all explained in Section 3. Section 4 explores features of a transition probability matrix, and the key concepts are discussed with examples. Section 5 presents the estimation results. Section 6 discusses several policy implications for the U.S. agriculture, and then concludes the paper by suggesting possible directions for further research. Appendix gives a detailed explanation of the χ^2 hypothesis testing procedure applied in the study.

2. Methods

2.1. A nonparametric regression

Consider a nonparametric regression model

$$y = m(x) + \epsilon \tag{2.1}$$

where x is a d dimensional vector of independent variables, ϵ is an error term. The conditional mean curve of (2.1) is $E[y|x] = m(x)$, where it is assumed that $E[\epsilon|x] = 0$. By definition, $m(x) = \int yf(y|x)dy = \int y\frac{f(y,x)}{f(x)}dy = \frac{\int yf(y,x)dy}{\int f(y,x)dy}$, where $f(x)$ is the unknown probability density function (pdf) of x, and $f(y,x)$ is the unknown joint pdf of x and y. The Nadaraya-Watson density estimation method is used to approximate these pdf's,[8] and next $m(x)$ is estimated by

$$y_\theta(x) = \sum_{i=1}^{n} y_i p_{i\theta}(x) \tag{2.2}$$

where

$$\begin{aligned} p_{i\theta}(x) &= \frac{K(\frac{X_i-x}{\theta})}{\Sigma_{i=1}^n K(\frac{X_i-x}{\theta})} \text{ if } \Sigma_{i=1}^n K(\frac{X_i-x}{\theta}) > 0 \\ &= 0 \text{ otherwise.} \end{aligned}$$

For purposes of implementation, we opt for a normal kernel,[9] where $K(\frac{x-X_i}{\theta})$ $= \frac{1}{\sqrt{2\pi}}\frac{1}{\theta\sigma_x} \exp\left[-\frac{1}{2}\left(\frac{X_i-x}{\theta\sigma_x}\right)^2\right]$. Here the term $K(\frac{x-X_i}{\theta})$ denotes the likelihood of x being the value actually associated with y_i, and the term $\Sigma_{i=1}^n K(\frac{x-X_i}{\theta})$ the likelihood of x being associated with any of the observation y_i.[10] The band width parameter θ controls each observation's influence on the prediction of y. For example, Eq. (2.2) would emphasize points nearby x if $p_{i\theta}(x)$ uses a small θ, and emphasize distant points if it uses a large θ. The optimal band width used in the calculations is determined by $\theta = (\frac{4}{n(d+2)})^{(\frac{1}{4+d})}$. The term σ_x is the standard deviation of x. Finally, the weight $p_{i\theta}(x)$ represents the probability of x associated with the i^{th} observation.

[8] See Silverman (1986) and Hardle (1990) for properties of the Nadaraya-Watson density estimation.

[9] Results are independent of the choice of the kernel density function $K(\frac{x-X_i}{\theta})$, since the predicted values will approach the true values as the number of observations increases and the band width gets smaller.

[10] **Assumption 1. Let** $\epsilon \equiv \frac{X_i-x}{\theta}$. (i) The distribution function $K : \Re \rightarrow \Re$ is Borel measurable, (ii) $\int K(\epsilon)d\epsilon = 1$ (i.e., integrates to one), (iii) $\int |K(\epsilon)|\, d\epsilon < \infty$ (i.e., boundedness), and (iv) $\lim_{\|\epsilon\|\rightarrow\infty} \| \epsilon \| K(\epsilon) = 0$ where $\| \epsilon \|$ is the Eucledian norm and $\sup_\epsilon |K(\epsilon)| < \infty$ (i.e., K vanishes outside a compact set).

Assumption 2. The band width θ is set optimally according to a function $\theta = \theta(n)$ such that $\lim_{n\rightarrow\infty} \theta(n) = 0$ and $\lim_{n\rightarrow\infty} n\theta(n) = \infty$.

Nonparametric estimations are based on the idea that observations close to x contain more information on $E[y|x]$ than those observations far away from x. The postulated form of the density function determines the shape of the regression function, $y_\theta(x)$. The choice of θ affects the magnitude of the weights assigned to observations in the neighborhood of x. For example, if θ is large, the observations far from x will have a large impact on $y_\theta(x)$ (Silverman, 1986; Hardle, 1990).

2.2. Markov chains

Consider a stochastic process $\{X_t, t = 0, 1, 2, ...\}$ that takes on a finite or countable number of values. Unless otherwise stated, this set of values of the process will be denoted by the set of nonnegative integers $\{0, 1, 2, ...\}$. If $X_t = i$, then the process is said to be in state i at time t.

Assumption 1 (Time-stationary transition probabilities). Whenever the process is in state i, there is a fixed probability p_{ij} that it will next be in state j : that is,

$$p\{X_{t+1} = j \mid X_t = i,\ X_{t-1} = i_{t-1},\ \dots\ , X_1 = i_1,\ X_0 = i_0\} = p_{ij} \tag{2.3}$$

for all states $i_0,\ i_1,\ \dots\ , i_{t-1},\ i, j$ and $t \geq 0$. Such a stochastic process is known as a *Markov chain*. Eq. (2.3) may be interpreted as stating that, for a Markov chain, the conditional distribution of any future state X_{t+1} given the past states $X_0, X_1, ..., X_{t-1}$ and the present state X_t, is independent of the past states and depends only on the present state. The value p_{ij} stands for the probability that the process will, when in state i, next make a transition into state j. Since the probabilities are nonnegative and since the process must make a transition into some state, we have $\Sigma_{j=0}^{\infty} p_{ij} = 1$ for $i = 0, 1, ...$ and $p_{ij} \geq 0$ for $i, j \geq 0$.

Assumption 2 (A first-order Markov chain). The stochastic process follows a first-order chain written as

$$X_{t+1} = PX_t \text{ where } P = (p_{ij}). \tag{2.4}$$

That is, the probability of a county being in a particular state at time $(t + 1)$ is solely a function of its state at time t. A second-order chain can similarly be defined as one in which the probability of a county being in a particular state at time $(t + 1)$ only depends on that county's states at times $(t - 1)$ and t.

If Assumptions 1 and 2 are satisfied,[11] then the time-stationary transition

[11] Testing procedures are provided in Appendix.

probabilities will be $p_{ij} = \left(\frac{n_{ij}}{n_i}\right)$ which solves the following maximization problem,

$$Max \prod_{i,j} p_{ij}^{n_{ij}} \text{ subject to } \Sigma_{j=1}^{m} p_{ij} = 1 \text{ for } i = 0, 1, 2, ..., m \text{ and } p_{ij} \geq 0.$$

n_{ij}^t denotes the number of counties moving from state i at time $(t-1)$ to state j at time t; $n_{ij} = \Sigma_{t=1}^{T} n_{ij}^t$ is the total number of counties moving from state i to state j over $t = 1, 2, ..., T$; and $n_i = \Sigma_{j=1}^{m} n_{ij}$ is the total number of counties that were in state i over $t = 0, 1, ..., T$ and $i = j = 1, ..., m$.

Existence and uniqueness of the time-invariant distribution, π. The $s-step-ahead$ distribution should evolve as

$$X_{t+s} = [P]^s X_t \tag{2.5}$$

where $[P]^s \to \pi$ as $s \to \infty$. (s denotes the number of iterations.) The presence of π guarantees that the process is independent of initial classification of observations, and that the elements of P no longer change from one period to the next, although counties may continue to alter their states over time.[12] Provided below are several definitions and a theorem, adopted from Hoel, Port, and Stone (1987), which are used to prove the existence and uniqueness of π.

Definition 2.1. *Class i is said to have period d if $p_{ij}^n = 0$ whenever n is not divisible by d, and d is the largest integer with this property. For instance, starting in i, it may be possible for the process to enter class i only at times $2, 4, 6, 8, ...$, in which case class i has period 2.*

Definition 2.2. *A class with period 1 is said to be $aperiodic$.*

Definition 2.3. *Class j is said to be $accessible$ from class i if $p_{ij}^n > 0$ for some $n \geq 0$.*

Definition 2.4. *Two classes i and j that are accessible to each other are said to $communicate$.*

Definition 2.5. *For any class i we let f_i denote the probability that, starting in class i, the process will ever reenter class i. Class i is said to be $recurrent$ if $f_i = 1$, and $transient$ if $f_i < 1$. Class i is recurrent if $\sum_{n=1}^{\infty} p_{ii}^n = \infty$ and transient if $\sum_{n=1}^{\infty} p_{ii}^n < \infty$.*

[12] Debreu and Herstein (1953) show properties of a transition (or stochastic) probability matrix at length.

Definition 2.6. *A Markov chain is said to be irreducible if there is only one grouping of classes; that is, if all classes communicate with each other.*

Definition 2.7. *If a class i is recurrent, then it is said to be* positive *recurrent if, starting in i, the expected time until the process returns to class i is finite. Positive recurrent, aperiodic classes are called ergodic.*

Theorem 2.8. *For an irreducible ergodic Markov chain, $\lim_{n\to\infty} p_{ij}^n$ exists and is independent of i. Furthermore, letting $\pi_j = \lim_{n\to\infty} p_{ij}^n$, $j \geq 0$, then π_j is the unique non-negative solution of $\pi_j = \sum_{i=0}^{\infty} \pi_i p_{ij}$, $j \geq 0$ and $\sum_{j=0}^{\infty} \pi_j = 1$.*

3. Description of data and variables

The data used in this study were obtained from the Census of Agriculture (USDA, 1992). The following variables were retrieved for each county over the three census periods 1982, 1987, and 1992: total sales of agricultural produce, harvested land in acres, and the number of farms. Sales were deflated by the annual consumer price index to obtain sales at constant prices. County i's farm size is defined as the ratio of harvested acres to the number of farms in that county. The productivity measures, sales per farm and sales per acre, are defined as the ratio of sales to the number of farms and the ratio of sales to the harvested acres, respectively. Each county is associated with five figures: average farm size, productivity per farm, productivity per acre, longitude, and latitude.

Since we are interested in the distributions (Figures 1, 3, 5) and less in the level of the variables, the following modifications were done in the original data to stratify (or classify) counties on the basis of minimum variance criterion (Cochran, 1966). We first remove the right-skewness prevalent in the original data on the size and productivity measures (Figures 1, 3, 5), next express the variables in natural logarithm, and then divide them by their respective means. The resulting distributions are plotted in Figures 2, 4, 6 making comparisons relatively easy as to how far a farm is away from the average farm represented by the value 1.0 on the horizontal axis. A farm with a value greater than 1.0 represents a larger-than-average farm or a more-productive-than-average farm.

The strata (or classes) required by the Markov chain model divide equally the range of the horizontal axis in Figure 2, 4, 6. Presented in Table 1 is an example of how the 6 cut-off points determined for the 7 strata of productivity per acre and are the associated values in constant 1990 US dollar for each census year. In this table, the value 0.850 represents the cut-off point for stratum 1 and the value 1.225 for the sixth stratum. The associated values of the original data are 161 in 1982 and 1521 in 1992, respectively.

Spatial variability is estimated using the grouping of U.S. states that is suggested by the USDA; and according to this, the 51 states are grouped in 9 divisions which in turn comprise four regions. The states of Alaska, Hawaii and Puerto Rico are excluded, due to their low level of agricultural activities and their geographical position. Table 2 gives in the first column this grouping and the number of valid observations in each stratum or class. Figure 7 gives the state map with the region and division classifications. Table 3 gives the average size and productivity at the national level, demonstrating that the two productivity measures increased by 100 percent as size increased only by 10 percent during the period of 1982-1992.

4. Dynamics of transition

In what follows we describe the main features of a transition probability matrix P calculated using productivity per acre at the national level and discuss the conditions under which this matrix represents an irreducible ergodic Markov chain. The same interpretations also apply to other transition matrices.

An element p_{ij} of P represents the probability that a farm will, when in state i at time t, next make a transition into state j at time $(t+1)$. The elements in the first row are denoted by p_{1j}, $j = 1, ..., 7$, where $p_{11} = 0.72$, $p_{12} = 0.27$, and $p_{13} = 0.01$. Of the entire sample of 5,878 farms over the period 1982-1992, a total of 426 farms fell in State 1. Of those farms, 72 percent (p_{11}) remained in that same state; 27 percent (p_{12}) moved into State 2; one percent (p_{13}) moved into State 3; and transition to States 4-7 did not occur in the following period. Similarly, of 5,878 farms, a total of 1,201 farms fell in State 2. Of 1,201 farms, 76 percent (p_{22}) remained in that same state, 16 percent (p_{23}) moved into State 3, one percent into State 4, and no transition occurred into States 5-7 in the following period.

The matrix P has seven states (or intervals). State 2 (corresponding to the interval $[0.85, 0.93]$) is *accessible* from State 1 (corresponding to the interval $[0, 0.85]$) since $p_{12} \neq 0$. States 1 and 2 are accessible to each other, hence they are said to *communicate*, and it is denoted by $1 \longleftrightarrow 2$. In fact, all of the seven states are communicating, implying that all of the states are in the same class. The Markov chain is then *irreducible* since there is only one class. It is easy to verify that P is irreducible. For example, it is possible to go from State 1 to State 7 through the path $1 \longleftrightarrow 2 \longleftrightarrow 3 \longleftrightarrow 4 \longleftrightarrow 5 \longleftrightarrow 6 \longleftrightarrow 7$. That is, one way of getting from

State 1 to State 7 is to go from State 1 to State 2 (with probability $p_{12} = 0.27$), then go from State 2 to State 3 (with probability $p_{23} = 0.16$),..., finally go from State 6 to State 7 (with probability $p_{67} = 0.17$).

Persistence is measured by the probabilities in the diagonal elements of P: large values for high, small values for low persistence. Over this one-period horizon, the predominant feature of P is high persistence among those farms in States 2 and 7, and low persistence in States 5 and 6, implied by the diagonal entries 0.76, 0.82, 0.55, and 0.59, respectively. This is interpreted as productivity tending to move away from the national average, roughly represented by States 4 and 5. A close look at the off-diagonal elements of P also reveals two patterns of movements. In the first pattern, farms tend to move toward States 2, 3, and 4. Consider, for example, 426 farms in State 1. Of these, 27 percent tend to move into State 2 and only 1 percent to State 3 in the following period; likewise, of 1,201 farms in State 2, 16 percent tend to move into State 3, while only one percent into State 4, and seven percent back into State 1. A similar pattern is also prevalent in States 3, 4, and 5. In the second pattern, farms in States 1 through 5 appear to move 2 states up, one state down. These two patterns are reflected in the time-invariant distribution. Persistence can also be measured using a *measure of mobility* $\mu : \mu(P) = (m - Trace(P))/(m-1) = (7 - 4.837)/6 = 0.36$ where m is the dimension of P, which is equal to 7. The lower the mobility μ is, the more persistence there is in P (Quah, 1993, 1996). The value 0.36 indicates that P is not significantly persistent.

The *time-invariant* distribution π characterizes the limiting behavior of farms as the number of iterations (s) of P goes to ∞. Nothing enforces existence or uniqueness of this distribution. That precisely one such distribution was found is a consequence of P at hand. Note that the invariant distribution can be read as projections of what will happen in the future, provided that policies remain unchanged for a sufficiently long period of time and that no unforeseen events occur. The invariant distribution obtained is ($\pi_1 = 0.06$, $\pi_2 = 0.27$, $\pi_3 = 0.27$, $\pi_4 = 0.19$, $\pi_5 = 0.08$, $\pi_6 = 0.06$, $\pi_7 = 0.06$). Everything else constant, this distribution states that in the final period, States 2, 3, and 4 should include 74 percent ($= \pi_2 + \pi_3 + \pi_4$) of 5,878 farms in the U.S. This establishes a right-skewed distribution in which there is a *peak* at States 2 and 3, suggesting that at the limit the majority of farms would move away from the national average productivity and that productivity would converge to a less-than-average level. Since there is only one peak to emerge, *polarization* should not be expected. If, however, there had been two peaks, one on the lower tail and the other on the upper tail of the invariant distribution, then coexistence of high and low-productivity farms would have been the conclusion. Finally, a comparison of the time-invariant distribution with the actual terminal period distribution,[13] which are almost identical, suggests the presence of a common tendency among U.S. farms with respect to the variable of interest.

The *speed of convergence*, measured by the second largest eigenvalue λ of P, is the rate at which the stochastic process converges to the time-invariant distribution.[14] (This concept is different from the one used in the convergence studies applying parametric regression method. Passing time in our context corresponds to the speed of convergence in the parametric regression.) In our example, the speed of convergence is equal to 0.938, which implies that time-invariant distribution is reached after few iterations of P. For example, if P is a diagonal matrix, then the number of iteration s will be zero since P is already in equilibrium. In other words, the further the matrix P is away from the equilibrium, the lower the speed of convergence will be, and hence the bigger the number of iterations will be.

Assumption 2, *time stationarity* of P, is tested by χ^2 statistic, which is explained in Appendix A in detail. If the calculated χ^2 is greater than the table value of $\chi^2_{m(m-1)(T-1)}$ where $T = 2$, then P is said to be stationary over time. In the case of a nonstationary P, one should examine time-specific transition matrices individually.

[13] The actual terminal period distribution is calculated as ($\pi_1 = \frac{426}{5{,}878} = 0.07$, $\pi_2 = \frac{1{,}201}{5{,}878} = 0.20$, $\pi_3 = \frac{1{,}730}{5{,}878} = 0.29$, $\pi_4 = \frac{1{,}268}{5{,}878} = 0.22$, $\pi_5 = \frac{565}{5{,}878} = 0.10$, $\pi_6 = \frac{345}{5{,}878} = 0.06$, $\pi_7 = \frac{343}{5{,}878} = 0.06$).

[14] Since the time-invariant distribution is the lefteigenvector corresponding to the (isolated) unit eigenvalue, the second eigenvalue would be the speed of convergence.

Transition probability matrix at the national level								
States	1	2	3	4	5	6	7	N
1	$\boxed{0.72}$	0.27	0.01					426
2	0.07	$\boxed{0.76}$	0.16	0.01				1,201
3		0.17	$\boxed{0.70}$	0.12	0.01			1,730
4			0.19	$\boxed{0.69}$	0.11	0.01		1,268
5				0.28	$\boxed{0.55}$	0.15	0.02	565
6				0.02	0.22	$\boxed{0.59}$	0.17	345
7					0.02	0.16	$\boxed{0.82}$	343
Invariant dist.	0.06	0.27	0.28	0.19	0.08	0.06	0.06	5,878
Iterations (s)	11							
χ^2	C-$\chi^2 = 68.96 >$ T-$\chi^2_{m(m-1)(T-1)} = 55.76$							
Eigenvalues	1.000	$\boxed{0.938}$	0.828	0.693	0.583	0.479	0.316	

where States 1 through 7 in the above transition matrix correspond to the intervals [0, 0.85), [0.85, 0.93), [0.93, 1.0), [1.0, 1.08), [1.08, 1.15), [1.15, 1.23), [1.23 and above], respectively.

5. Empirical results

5.1. Spatial patterns during 1982-92

For each time period separately, a cross-section nonparametric regression model is applied to investigate geographical patterns. For example, to examine patterns in productivity per acre in the period 1982 we estimate a cross-section regression model with productivity per acre as the dependent variable and longitude and latitude as the independent variables. We further repeat the same regression model for the periods 1987 and 1992 and obtain a total of three estimations for productivity per acre. To this end, a total of nine regression models are estimated as there are three independent variables (productivity per acre, farm size, and productivity per farm) and three time periods (1982, 1987, and 1992). The estimation results are then presented in colored graphs.

Productivity per acre. The period of 1982-1992 can be characterized by a three-layer productivity pattern at the national level. The first layer, which shows the highest productivity, starts from California, Arizona, Oregon, and Florida in 1982 (Figure 8), includes New Mexico, Washington, north of Georgia, Connecticut, and Maine in 1987 (Figure 9), and finally expands in 1992 to the west and east coasts and south of the U.S. (Figure 10). The second layer reflects the middle range productivity, stretching from west to east; and the third layer, which reveals the lowest productivity, dominates over the states in up north close to Canada (Figures 8, 9, 10). At the regional level, the West has always been the leading region in productivity, followed by the South and the Northeast. The Midwest, on the contrary, continuously remained at the bottom of the productivity scale. At the divisional level, according to the 1992 estimations illustrated in Figure 10, the Pacific division in West occupies the best position in productivity, East South Central and South Atlantic in South the second, New England and Middle Atlantic in Northeast the third, West South Central in South the fourth, Mountain in West the fifth, West South Central in Midwest the sixth, and West North Central in Midwest the seventh.

Farm size. Figures 11, 12, and 13 show that size distribution to large extent remained unchanged in the period 1982-1992. This distribution is characterized by large farms in the middle belt and small farms in the East, West and South regions. With a size ranging from 300 to 1,000 acres, large farms appear especially in the states of North Dakota, South Dakota, Nebraska, Kansas, Minnesota, and Iowa in the Midwest; Montana, Wyoming, Washington, Nebraska, Idaho, and Colorado in the West; and Texas, Oklahoma, and Arizona in the South, while small farms in the range of 0-200 acres are especially clustered in the Northeast and in East South Central and South Atlantic divisions of the South, and in the Pacific division of the West.

Productivity per farm. As can be seen from Figures 14, 15, and 16, productivity per farm has continuously increased during the period 1982-1992. In 1982, high productivity was realized only in few states in the West and Midwest regions (Figure 14), but in 1992 the large majority of states experienced high productivity ranging from 150 to 450 thousand \$ (Figure 16). This suggests that the number of farms dropped rapidly in the period 1982-92. Productivity has steadily risen across all the regions, especially in a circle of states, including California, Arizona, New Mexico, Colorado, Kansas, Nebraska, Wyoming, Idaho, and Nevada. Revealed by this is the fact that a large number of farms in the dry area of the U.S. have suspended farming activities, and this increased productivity per farm. Similar observation is also prevalent in North Carolina, Florida, Texas, Washington, Montana, and Maine.

Inverse relation. A pairwise comparison of Figures 8 and 11, Figures 9 and 12, and Figures 10 and 13 indicates a persistent inverse relation between size and productivity per acre. This relation appears to get stronger towards 1992. (When productivity is measured in per farm unit, the inverse relation is not so apparent.)

The inverse relation was investigated parametrically as well. Reported in Table 4 are correlation coefficients which are all negative, supporting in general the assertion that at all levels large farms were relatively less productive than small ones.

5.2. Convergence: projection into the future

Comparison of national and regional productivity per acre. The dark and thick lines in Figures 17, 18, 19 represent time-invariant distributions for productivity per acre, productivity per farm, and farm size at the national level, and the light and dashed lines represent the same variables at the regional level. As is shown in Figure 17, time-invariant distribution for productivity per acre is right-skewed at both national and regional levels, with a stronger tendency at the national level. From a regional perspective, convergence to a level lower than the respective regional average is especially pronounced in the Northeast and Midwest and less pronounced in the South and West. As can be seen from Figure 19, when productivity is measured at the farm level, convergence to the averages arises at the national and regional levels. But this should not be regarded as evidence that productivity per farm is likely to equalize across regions. This can only be interpreted as evidence that the-then-regional-averages act as the long run center of gravity since the regions are very likely to differ in the future with respect to their productivity level per farm.

Comparison of national and regional farm size. Figure 18 illustrates a mixed picture with respect to farm size. At the national level, small and large farms are likely to coexist (i.e., one peak in the lower tail, the other on the upper tail of the distribution), while at the regional level small farms in the South and large farms in the other three regions are likely to emerge. Surprisingly, medium-sized farms tend to disappear in the long run. These regional differences reflect in some way distinct farming activities, such as Northeast dominated by high value products, South by grains, crops, and fruits, Midwest by dairy products, and West by fruits and vegetables.

Comparison of regional and divisional distributions. The dark and thick lines in Figures 20 through 31 represent time-invariant distributions for productivity per acre, productivity per farm, and farm size at the regional level, and the light and dashed lines represent the same variables at the divisional level. Predictions for the Northeast region and its divisions are illustrated in Figures 20-22. According to Figure 20, in the Northeast, productivity per acre converges to a level smaller than the regional average, and this relation also holds at the divisional level. Figure 22 suggests that convergence to the regional and divisional averages of productivity per farm is likely to occur at the regional and divisional levels, and finally Figure 21 illustrates that with respect to farm size distribution the Middle Atlantic division determines the size and productivity distributions at the regional level.

Projections for the Midwest and its divisions are illustrated in Figures 23-25. At the regional (divisional) level, productivity per acre moves towards the smaller-than-regional (divisional) average, whereas with a bell-shaped curve at the regional (divisional) level productivity per farm reveals converges to the regional (divisional) average. Finally, farm size is likely to increase to the higher-than-regional average (Figure 24). Distribution for the regional productivity per acre is determined by the East North Central division, whereas the regional size distribution determined by the West North Central.

Projections for the South and its divisions are illustrated in Figures 26-28. Productivity per acre and farm size converge to the smaller-than-regional average as productivity per farm converges to the regional average. With respect to productivity per acre, the regional and divisional distributions look alike, except for the East South Central division. A similar exception also arises with respect to farm size in the East South Central division, where size is expected to evolve around a level slightly smaller than the regional average. For the other two divisions, size is expected to be around a level much smaller than the regional average. For productivity per farm, the divisional distributions are almost identical to the regional one. It appears that the West South Central is the leading division in determining the regional farm size.

Predictions for the West and its divisions are illustrated in Figures 29-31. Productivity per acre and productivity per farm both converge to the regional average, while size shows polarization around two peaks. One emerges around the smaller-than, the other around the larger–than-regional average size. With respect to productivity per acre, both divisions are anticipated to be around the regional average, but the Mountain division has slightly more pronounced effect on the whole region.

5.3. Inverse relation: projection into the future

In the context of Markov chains, a long run negative (positive) relationship between size and productivity per acre is said to exist if their time-invariant distributions are skewed in the opposite (same) directions.[15]

National analysis. An unclear relation between size and productivity arises at the national level when their invariant distributions are compared. Productivity has a right-skewed time-invariant distribution, represented by the dark and thick line in Figure 17 as farm size has a distribution with two peaks shown in Figure 18. This suggests that the long run productivity is most likely to stabilize at a level lower than the average, whereas regarding farm size large and small farms are expected to coexist.

Regional analysis. Three observations are immediate when the regional time-invariant distributions for size and productivity are compared. First, a positive relation emerges in the South, an inverse relation in the Northeast and Midwest, and an unclear relation in the West. With the right-skewed distributions, illustrated in Figures 26 and 27, the South manifests a typical positive relation at the regional as well as divisional levels. In this region, farms incline to get smaller as they become less productive than the average farm. In the Northeast, farm size and productivity are negatively related, illustrated in Figures 20 and 21. The Middle Atlantic division plays a dominant role in this relation, reflected by the fact that its invariant distribution mimics the regional distribution. The Midwest, illustrated in Figures 23 and 24, is the region where a typical inverse relation is observed not only at the regional but also divisional level. One peak emerges in both size and productivity, appearing on the opposite sides of the invariant distributions. In the West, productivity converges to the average at the regional and divisional levels (Figure 29), but size wiggles in the region and the Mountain division as it converges to the average in the Pacific division (Figure 30).

6. Comments and conclusions

This study examined the patterns of farm size and productivity in U.S. agriculture over the period 1982-1992, and projected these ex post patterns into the future. The examination was carried out at the divisional, regional, and national levels. First, a nonparametric kernel regression method was applied to detect ex post geographical patterns in changes of size and productivity. Estimations show that (i) in 1982 productivity per acre was high in the East, West, and South, modest in the middle part of the U.S., and low in the North, and this pattern remained the same in the period 1987-1992, while the level of productivity continuously

[15] Note that in the following paragraphs the inverse relationship is investigated only by comparing farm size with productivity per acre.

increased over time; (ii) during 1982-1992 farm size remained unchanged, large farms being in the middle belt stretching from north to down south and small ones in the East, West and South; and finally (iii) over the period 1982-1992 an inverse relationship grew stronger between size and productivity per acre. Furthermore, Markov chain method was employed to project the ex post patterns into the future. Predictions suggest that at the national and regional levels (i) farms are likely to experience lower productivity per acre; (ii) small and large farms are likely to coexist as medium-sized farms tend to vanish; and lastly (iii) the relationship between size and productivity is predicted to be negative in the Northeast and Midwest regions, positive in the South, and unclear in the West and nation wide.

These results shed light on several issues hotly discussed among academicians and among policy makers. First, long lasting academic curiosity that small farms are more productive than large farms seems to be a locational phenomenon, not necessarily a stylized fact nor a spurious result caused by bias due to the omission of land quality.[16] During the period 1982-1992 the IR has been observed all over the U.S., but in the future it is expected that such relationship would hold only in the Northeast and Midwest regions. In the context of off-farm work participation, Tavernier, Temel, and Li (1997) has also estimated the IR in the Northeast during the same period. The fact that the Northeast is highly populated, relatively poorly endowed with farm land, and highly urbanized leads to increasing land prices. Naturally, farms opt for specialization in high-value agricultural produce, like greenhouse farming, resulting in higher productivity per acre in small farms than productivity in large farms. Agricultural and environmental regulations that prohibit the conversion of farm land into urban use further become restrictive for large farms, in view of a severe need in the Northeast for out-of-state labor during the harvest time. On the contrary, an expected positive relationship in the South can partly be attributed to upcoming changes in farming structure, not necessarily to better farm management nor better supervision of large farms. Possibly, these changes have already been implanted in the farming sector through past macro policies and developments, including changes in interest rates, continuously increasing returns in financial markets, the introduction and adoption of new technologies, changes in regulations with respect to tax exemption and direct government subsidies, and developments in labor markets. All in all, an assessment of the relationship between size and productivity should consider multiple

[16] In an ongoing research, we investigate the IR from an ecological perspective, estimating the relationship between size and productivity over three agro-ecological zones in the U.S. By doing so, soil, land, and climate conditions of an agro-ecological zone are taken into account.

factors, and give special emphasis to management of location-specific resources and the effects on the utilization of these resources of changes in domestic terms of trade between agriculture and nonagriculture.

A second issue, which relates to the future distribution of farm size, has remained on the agenda of policy makers for a long time. Policy makers have clearly been favoring the dominance of family farms, usually small scale, over large scale corporate enterprises, and this preference has even been formulated as a policy of the U.S., approved by the Congress. The Food and Agriculture Act of 1977 includes the following declaration: "Congress hereby specifically reaffirms the historical policy of the US to foster and encourage the family farm system of agriculture in this country. Congress firmly believes that the maintenance of the family farm system is essential to the social well-being of the Nation and the competitive production of adequate supplies of food and fiber. Congress further believes that any significant expansion of non-family owned, large scale corporate enterprises will be detrimental to the national welfare." Although small family farms have been favored, at least emotionally and politically, for almost a quarter of a century, their full dominance in agricultural markets is still questionable. Our finding from Markov chain method indicates that in the future small and large farms are likely to coexist and medium-seized farms to vanish at the national level, whereas at the regional level small farms are likely to be dominant in the South, large farms in the other three regions.

With respect to growth in farm size, often neglected in the literature is to uncover factors that are associated with farmers' risk taking behavior and with their performance under uncertainty. In this connection, a special emphasis needs to be given to the effects on farm size of such variables as the timing of operations, labor management and supervision, the exercise of control in a biological context (i.e., control over diseases, pests, and other natural hazards) on one hand and financial on the other. An additional factor, whose significance was empirically shown by Kislev and Peterson (1982) in the context of the long run growth in the U.S. agricultural firm size, is changes in relative factor prices. In their study, they showed that virtually all of the growth in firm size is explained by this factor, without reference to technological change or economies of scale.

A third issue concerns the expected geographical patterns in productivity per acre. Our results suggest that at the national and regional levels, productivity has a tendency to decline in the long run. In other words, productivity is not expected to show a regional pattern, one which is high in one region and low in the other, although these expectations grew out of a strong regional orientation.

High productivity first appeared among the farms in California and Arizona in the West, in Florida in the South, and Connecticut in the Northeast, and in subsequent years it grew stronger around these regional hubs.

A fourth remark relates to the future of U.S. farm organization. The shrinking number of young people raised on farms during the period 1982-97 may lead in the future to more nontraditional farm entrants, such as diversified nonfarm business entities, farm corporations, or vertically integrated food processing or marketing firms (Gale, 1993). This may presage a shift in the social and economic organization of U.S. farming away from the traditional arrangements where one person or family owns, operates, and provides most of the labor for a single farm toward increased specialization and concentration of ownership.

Finally, exit from farming has gained momentum in the 1980s, following a general increase during the 1970s. Also estimated for the 1990s is the shrinking in the pool of potential entrants. As reported by Gale (1993), during the period 1982-1987 entry of farmers less than 25 years old and 25-34 years old fell by 30 and 50 percent, respectively. Varying in the range 36-59 percent for less than 25 years age and in the range 8-41 percent for between 25-34 years age, this decline has mostly seen in the states of the Midwest and Texas in the South. The number of 20-24 year-old males raised on farms will shrink 25 percent in the period 1982-1987, 38 percent in the 1987-1992, and 19 percent in the 1992-1997. The decrease in the number of 25-34 year-old will be 9 percent in the 1982-1987, 18 percent in the 1987-1992, and 31 percent in the 1992-1997. These declines might be considered signs of increasing financial barriers and better nonfarm opportunities.

This study, of course, cannot be viewed, nor is it presented, as conclusive. Additional research is needed to specify more precisely the relationship between size and productivity across ecological zones. This should provide insights into the role that soil, land, and climate conditions play in agricultural production. A second field that deserves further research relates to methodological development. A challenging task for future research in this respect is to extend the Markov chain method in such a way that more specific management and human capital variables can also be included in the analysis to explain the transition in farm size and productivity. It is clear that estimating the specific effects of such factors requires a dynamic analysis.

References

[1] Barrett, C. (1993). *On the price risk and the inverse farm size-productivity relationship* (Staff Paper No. 369). Wisconsin: University of Wisconsin-Madison, Department of Agricultural Economics.

[2] Binswanger, H., & Rozensweig, M. (1986). Behavioral and material determinants of production relations in agriculture. *Journal of Development Studies*, 22, 503-539.

[3] Chavas, J. P., & Cox, T. (1988). A nonparametric analysis of agricultural technology. *American Journal of Agricultural Economics, 70,* 303-310.

[4] Cochran, W. (1966). *Sampling techniques*. New York: John Wiley & Sons. Inc. (2nd edition).

[5] Cornia, G. (1985). Farm size, land yields, and the agricultural production function: An analysis for fifteen developing countries. *World Development, 13,* 513-534.

[6] Cox, T., & Chavas, J. P. (1990). A nonparametric analysis of productivity: The case of US agriculture. *European Review of Agricultural Economics, 17,* 449-464.

[7] Debreu, G. & Herstein, I.N. (1953). Non-negative square matrices. *Econometrica, 21,* 597-607.

[8] de Janvry, A. (1987). Farm structure, productivity, and poverty (Working Paper no. 432). Berkeley, CA: University of California, Giannini Foundation of Agricultural Economics.

[9] de Janvry, A., Fafchaamps, M., & Sadoulet, E. (1991). Peasant household behavior with missing markets: Some paradoxes explained. *Economic Journal, 101,* 1400-1417.

[10] Dismukes, R., Harwood, J. L., Bentley, S. E. (1997). Characteristics and risk management needs of limited-resource and socially disadvantaged farmers (Agriculture Information Bulletin No. 733). Commercial Agriculture Division, Economic Research Service, and Risk Management Agency, U.S. Department of Agriculture.

[11] Eckstein, S., Donald, G., Horton, D., & Caroll, T. (1978). Land reform in Latin America: Bolivia, Chile, Mexico, Peru, and Venezuela (World Bank Staff Working Paper No. 275). Washington, D.C.: World Bank.

[12] Edwards, C., Smith, M. G., & Patterson, R. N. (1985). The changing distribution of farms by size: A Markov analysis. *Agricultural Economics Resources, 37*, 1-16.

[13] Eswaran, M., & Kotwal, A. (1986). Access to capital as a determinant of the organization of production and resource allocation in an agrarian economy. *Economic Journal*, 96, 482-498.

[14] Evenson, R. E., & Huffman, W. B. (1997). *Long-run structural and productivity change in U.S. agriculture: Effects of prices and policies.* Unpublished manuscript, Yale-Economic Growth Center at New Haven.

[15] Fawson, C., & Shumway, R. C. (1988). A nonparametric investigation of agricultural production behavior for U.S. subregions. *American Journal of Agricultural Economics, 70, 311-317.*

[16] Feder, G. (1985). The relation between farm size and farm productivity: The role of family labor, supervision and credit constraints. *Journal of Development Economics, 18,* 297-313.

[17] Gale, F. F. (1993). Why did the number of young farm entrants decline? *American Journal of Agricultural Economics, 75, 138-146.*

[18] Garcia, P., Offutt, S. E., & Sonka, S. T. (1987). Size distribution and growth in a sample of Illinois cash grain farms. *American Journal of Agricultural Economics, 69*(2), 471-476.

[19] Gardner, D. B., & Rope, R. D. (1978). How is scale and structure determined in agriculture? *American Journal of Agricultural Economics, 60*(2), 295-302.

[20] Goodman, A. L., & Anderson, W. T. (1957). Statistical inference about Markov chains. *The Annals of Mathematical Statistics, XXVIII*, 89-110.

[21] Goodman, A. L. (1962). Statistical methods for analyzing processes of change. *The American Journal of Sociology, 68*, 57-78.

[22] Hardle, W. (1990). *Applied nonparametric regression.* New York: Cambridge University Press.

[23] Harris, G. D., & Nehring, R. F. (1976). Impact of farm size on the bidding potential for agricultural land. *American Journal of Agricultural Economics, 58,* 161-69.

[24] Hoel, P. G., Port, S. C., & Stone, C. J. (1987). *Introduction to stochastic processes.* Illinois: Waveland Press, Inc.

[25] Hoppe, R. A., Green, R. C., Banker, D., Kalbacher, J. Z., & Bentley, S. E. (1993). Structural and financial characteristics of U.S. farms, 1995: 18th annual family farm report to the congress (Agriculture Information Bulletin No. 728). Rural Economy Division, Economic Research Service, U.S. Department of Agriculture.

[26] Keyzer, M. A., & Sonneveld, B. G. J. S. (1997). Using the mollifier method to characterize data sets and models: The case of the universal soil loss equation. *ITC Journal, 97*(3-4), 263-272.

[27] Kislev, Y., & Peterson, W. (1982). Prices, technology, and farm size. *Journal of Political Economy, 90*(31), 578-595.

[28] Lipton, M. (1993). Land reform as commenced business: the evidence against stopping. *World Development*, 21(4), 641-657.

[29] Quah, D. (1993). Empirical cross-section dynamics in economic growth. *European Economic Review, 37*(2-3), 426-34.

[30] Quah, D. (1996). Empirics for economic growth and convergence. *European Economic Review, 40,* 1353-1375.

[31] Peterson, L. W. (1997). *Are large farms more efficient?* (Staff Papers No. P97-02). Minnesota: University of Minnesota, Department of Applied Economics.

[32] Repetto, R., & Holmes, T. (1983). The role of population in resource depletion in developing countries. *Population and Development Review,* 9(4), 609-632.

[33] Silverman, B. W. (1986). *Density estimation for statistics and data analysis.* New York: Chapman and Hall.

[34] Sommer, J. E., Hoppe, R. A., Green, R. C., & Korb, P. J. (1995). Structural and financial characteristics of U.S. farms, 1995: 20th annual family farm report to the congress (Agriculture Information Bulletin No. 746). Resource Economics Division, Economic Research Service, U.S. Department of Agriculture.

[35] Stanton, F. B. (1978). Perspective on farm size. *American Journal of Agricultural Economics, 60,* 727-37.

[36] Taslim, M. (1989). Supervision problems and the size-productivity relation in Bangladesh agriculture. *Oxford Bulletin of Economics and Statistics, 51,* 55-71.

[37] Tavernier, M. E., Temel, T., & Li, F. (1997). The role of farm ownership in off-farm work participation. *Agricultural and Resource Economics Review,* 26(1), 67-81.

[38] USDA. (1992). CD-Rom by USDA. Washington, DC: U.S. Department of Agriculture.

[39] Yatchew, A. (1998). Nonparametric regression techniques in economics. *Journal of Economic Literature, XXXVI,* 669-721.

A. Assumptions of Markov chains

Here we present hypothesis testing procedures, adopted from Anderson and Goodman (1957) and Goodman (1962), to investigate whether or not the transition probability matrices at hand are time-stationary and follow a first-order process. For illustrative purposes, the following contingency table will be referred to throughout this Appendix:

$$A(t) = \begin{array}{|l|ll|l|}\hline \text{States} & 1_t & 2_t & \text{Total} \\ \hline 1_{t-1} & n_{11}^t & n_{12}^t & n_{1.}^t \\ 2_{t-1} & n_{21}^t & n_{22}^t & n_{2.}^t \\ \hline \text{Total} & n_{.1}^t & n_{.2}^t & n^t \\ \hline \end{array} \quad \text{and} \quad Z_i = \begin{array}{|l|ll|}\hline t/j & j=1 & j=2 \\ \hline t=1 & \hat{p}_{i1}^1 & \hat{p}_{i2}^1 \\ t=2 & \hat{p}_{i1}^2 & \hat{p}_{i2}^2 \\ t=3 & \hat{p}_{i1}^3 & \hat{p}_{i2}^3 \\ \hline \end{array} .$$

If $T = 3$, then we will have 3 contingency tables, $A(t)$ for $t = 1, 2, 3$, given two states $i = j = 1, 2$. In this example, $n_{ij} = \Sigma_{t=1}^3 n_{ij}^t$ and $n_i = \Sigma_{j=1}^2 n_{ij} = \Sigma_{t=1}^3 n_{i.}^t$

Assumption 1. The transition probabilities are time-stationary. Here the null hypothesis is $H_0 : p_{ij}^t = \hat{p}_{ij}$ for all t, and an alternative to this assumption is that the transition probability depends on t, $H_1 : p_{ij}^t = \hat{p}_{ij}^t$ where $\hat{p}_{ij}^t = \left(\frac{n_{ij}^t}{n_i^{t-1}}\right)$ is the estimate of the transition probability for time t. Under these hypotheses, the likelihood ratio is of the form, $\lambda = \Pi_t \Pi_{i,j} \left[\frac{\hat{p}_{ij}}{\hat{p}_{ij}^t}\right]^{n_{ij}^t}$, where $\Pi_{t=1}^T \Pi_{i,j} \hat{p}_{ij}^{n_{ij}^t}$ hold under H_0 and $\Pi_{t=1}^T \Pi_{i,j} (\hat{p}_{ij}^t)^{n_{ij}^t}$ holds under H_1. And $-2\log\lambda$ is distributed as $\chi^2_{(T-1)[m(m-1)]}$ when H_0 is true. It should be noted that the likelihood ratio resembles likelihood ratios obtained for standard tests of homogeneity in contingency table $A(t)$. The null hypothesis states that the random variables represented by the T rows in Z_i have the same distribution. In order to test it, we calculate $\chi_i^2 = \Sigma_{i,j} n_i^{t-1} (\hat{p}_{ij}^t - \hat{p}_{ij})^2 / \hat{p}_{ij}$. If H_0 is true, χ_i^2 has the limiting distribution with $(m-1)(T-1)$ degrees of freedom, and the set of χ_i^2 's is asymptotically independent, and the sum, $\chi^2 = \Sigma_{i=1}^2 \chi_i^2 = \Sigma_i \Sigma_{t,j} n_i^{t-1} (\hat{p}_{ij}^t - \hat{p}_{ij})^2 / \hat{p}_{ij}$, has the usual limiting distribution with $(T-1)[m(m-1)]$ degrees of freedom.

Another way of testing the same hypothesis is to calculate $\lambda_i = \Pi_{t,j} \left[\frac{\hat{p}_{ij}}{\hat{p}_{ij}^t}\right]^{n_{ij}^t}$ for $i = 1, 2$ by using Z_i. The asymptotic distribution of $-2\log\lambda_i$ is χ_i^2 with $(m-1)(T-1)$ degrees of freedom. The test criterion based on λ can then be written as $\Sigma_{i=1}^m - 2\log\lambda_i = -2\log\lambda$.

Assumption 2. The Markov chain is of a given order. Intuitively speaking, this assumption states that the location of a county at time $(t+1)$ is independent of its location at time t. A Markov chain is second-order if a county is in class

i at time $(t-2)$, in j at time $(t-1)$, and in k at time t. Let p^t_{ijk} denote the probability that a county follows a second-order chain. Time stationarity then implies $p^t_{ijk} = p_{ijk}$ for all $t = 2, \ldots, T$. A first-order stationary chain is a special case of second-order chain, one for which p^t_{ijk} does not depend on i.

Now let n^t_{ijk} be the number of counties in class i at $(t-2)$, in class j at $(t-1)$, and in class k at t. Let $n^{t-1}_{ij} = \Sigma_k n^t_{ijk}$ and $n_{ijk} = \Sigma^T_{t=2} n^t_{ijk}$. The maximum likelihood estimate of p_{ijk} for stationary chains is $\hat{p}_{ijk} = (n_{ijk}/\Sigma^m_{l=1} n_{ijl}) = \left(\Sigma^T_{t=2} n^t_{ijk}/\Sigma^T_{t=2} n^{t-1}_{ij}\right)$. The null hypothesis in this case is $H_0 : p_{1jk} = p_{2jk} = ... = p_{mjk} = p_{jk}$ for $j, k = 1, \ldots, m$. The likelihood ratio test criterion is $\lambda = \Pi^m_{i,j,k=1} \left[\frac{\hat{p}_{jk}}{\hat{p}_{ijk}}\right]^{n_{ijk}}$ where $\hat{p}_{jk} = (\Sigma^m_{i=1} n_{ijk}/\Sigma^m_{i=1}\Sigma^m_{l=1} n_{ijl}) = \left(\Sigma^T_{t=2} n^t_{jk}/\Sigma^{T-1}_{t=1} n^t_j\right)$ is the maximum likelihood estimate of p_{jk}. Under the null hypothesis, $-2\log\lambda$ has an asymptotic- $\chi^2_{m(m-1)^2}$ distribution where $\chi^2_j = \Sigma_{i,k} n^*_{ij}(\hat{p}_{ijk} - \hat{p}_{jk})^2/\hat{p}_{jk}$ and $n^*_{ij} = \Sigma_k n_{ijk} = \Sigma_k \Sigma^T_{t=2} n^t_{ijk} = \Sigma^T_{t=2} n^{t-1}_{ij} = \Sigma^{T-1}_{t=1} n^t_{ij}$ with $(m-1)^2$ degrees of freedom. The corresponding test using the likelihood ratio is $\lambda_j = \Pi^m_{i,k=1}\left[\frac{\hat{p}_{jk}}{\hat{p}_{ijk}}\right]^{n_{ijk}}$. The asymptotic distribution of $-2\log\lambda_j$ is chi-square with $(m-1)^2$ degrees of freedom.

To test the joint hypothesis $H_0 : p_{ijk} = p_{jk}$ for all $i, j, k = 1, 2, \ldots, m$, we calculate $\chi^2 = \Sigma^m_{j=1}\chi^2_j = \Sigma_{j,i,k} n^*_{ij}(\hat{p}_{ijk} - \hat{p}_{jk})^2/\hat{p}_{jk}$ which has the limiting distribution with $m(m-1)^2$. Similarly, the joint test criterion is $\Sigma^m_{j=1} - 2\log\lambda_j = -2\log\lambda = 2\Sigma_{j,i,k} n_{ijk}[\log\hat{p}_{ijk} - \log\hat{p}_{jk}]$.

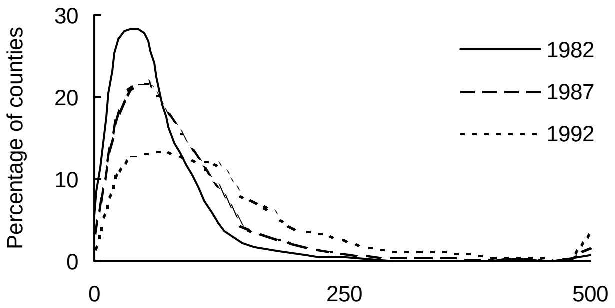


Figure 1. Productivity per farm ('000 $)

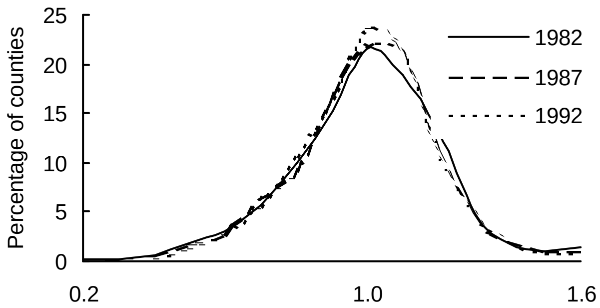


Figure 2. Productivity per farm (transformed)

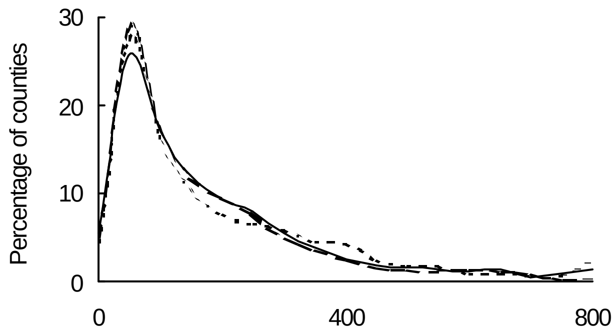


Figure 3. Size per farm (acres)

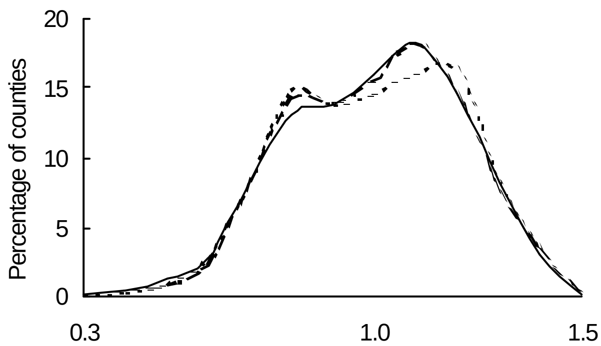


Figure 4. Size per farm (transformed)

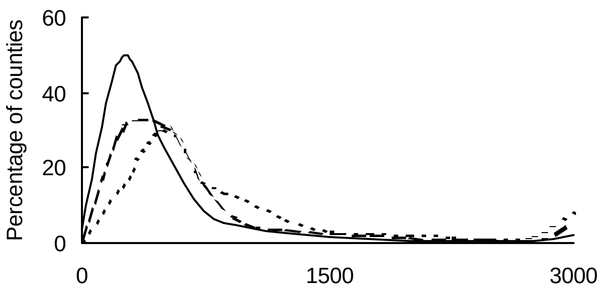


Figure 5. Productivity per acre ($)

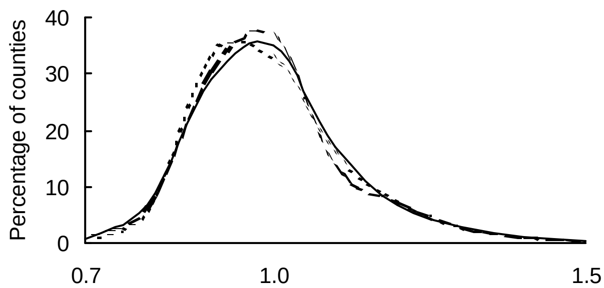


Figure 6. Productivity per acre (transformed)

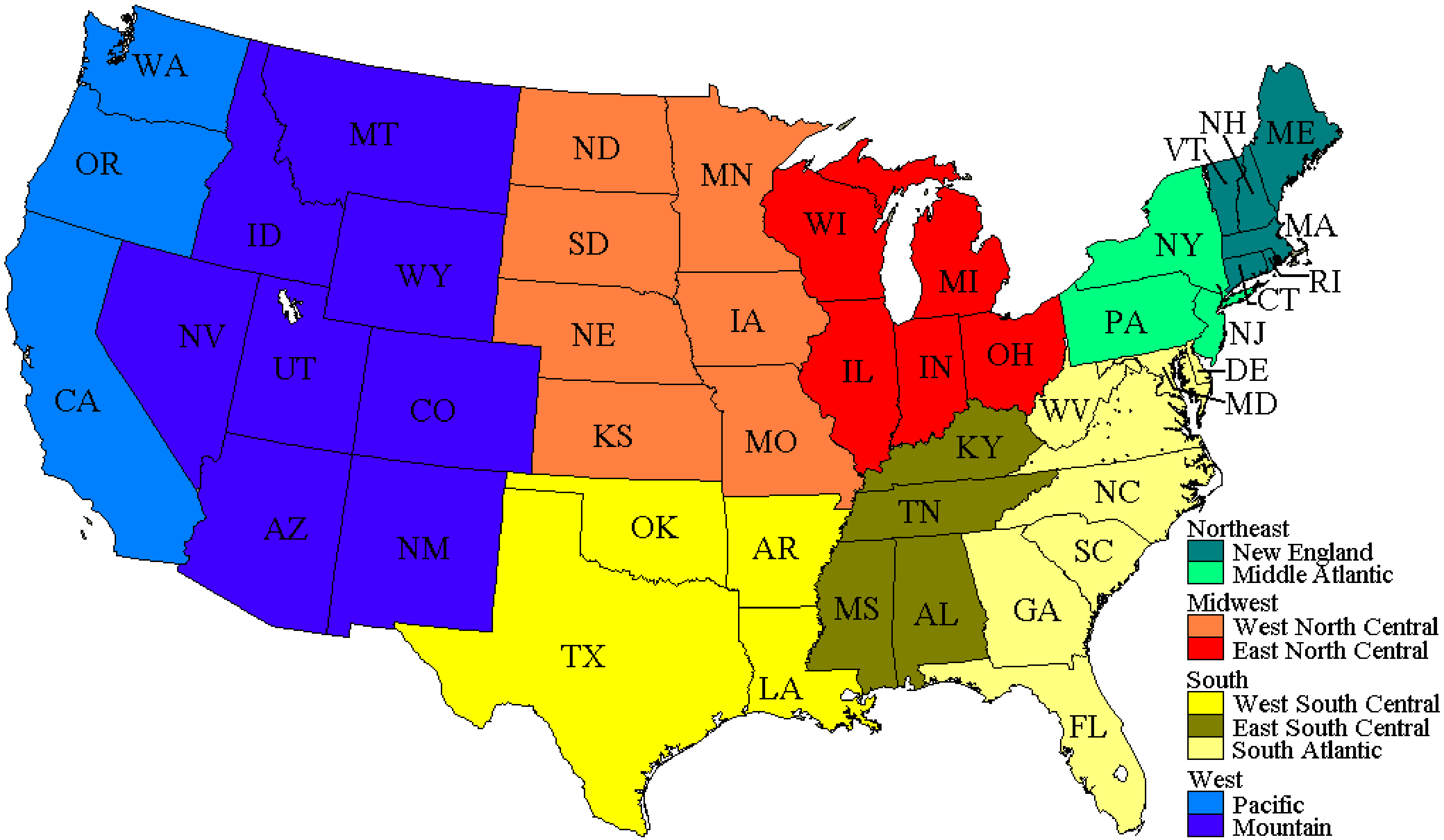


Figure 7. USA: regions and divisions

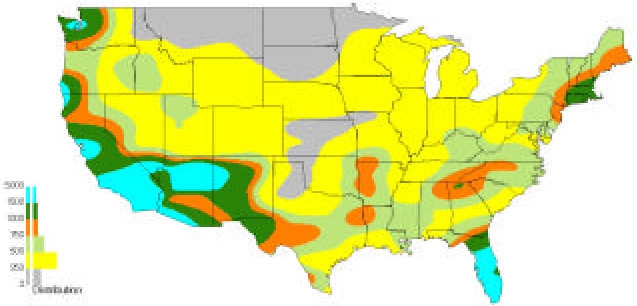


Figure 8. Productivity per acre in 1982 ($)

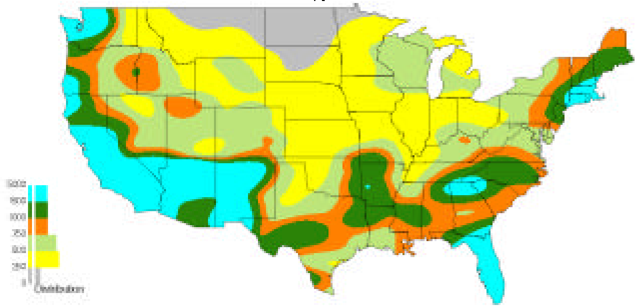


Figure 9. Productivity per acre in 1987 ($)

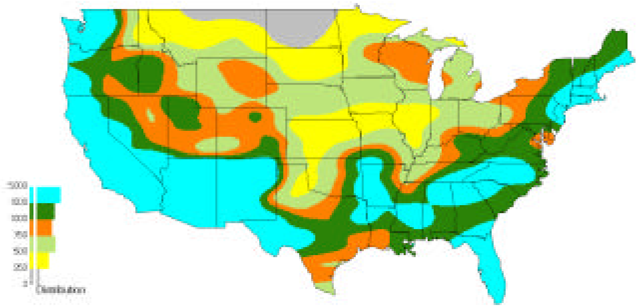


Figure 10. Productivity per acre in 1992 ($)

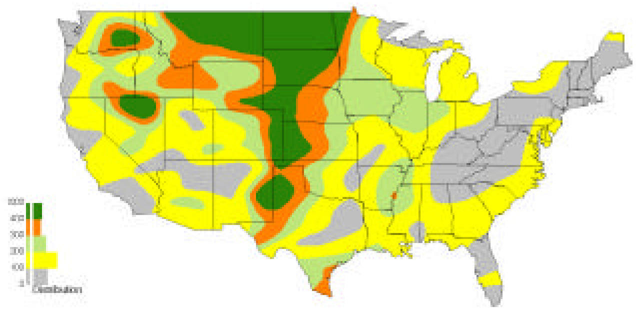


Figure 11. Size per farm in 1982 (acres)

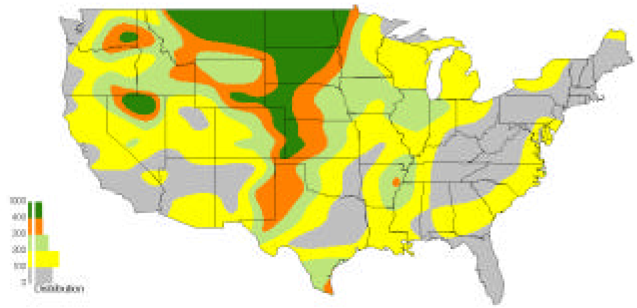


Figure 12. Size per farm in 1987 (acres)

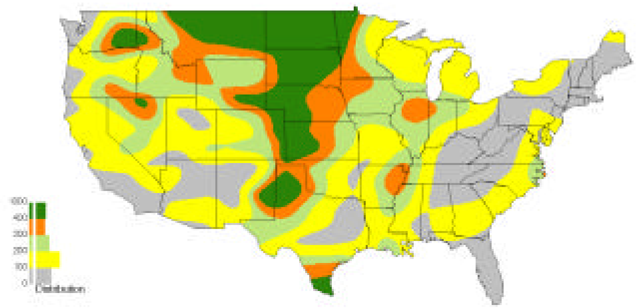


Figure 13. Size per farm in 1992 (acres)

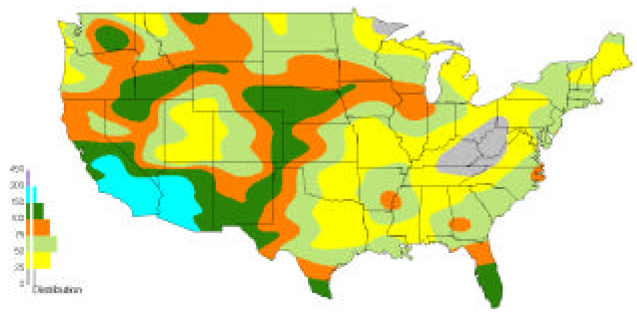


Figure 14. Productivity per farm in 1982 ('000 $)

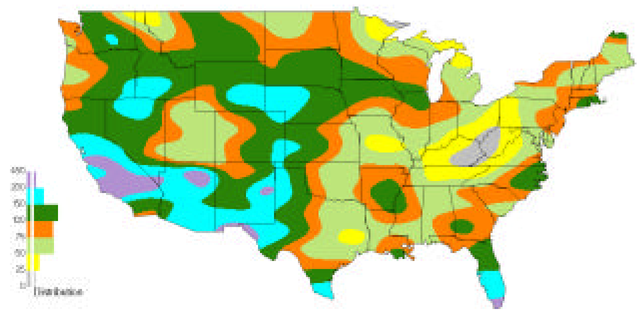


Figure 15. Productivity per farm in 1987 ('000 $)

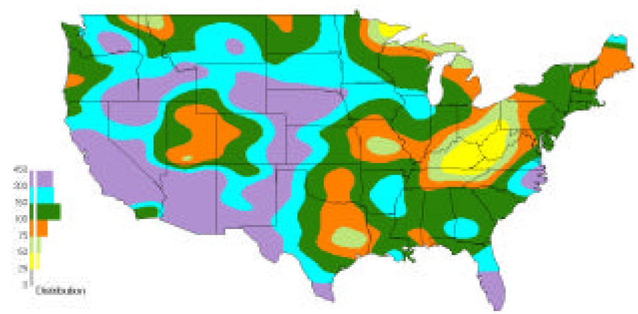
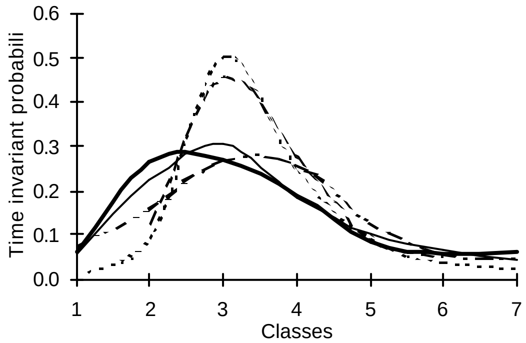
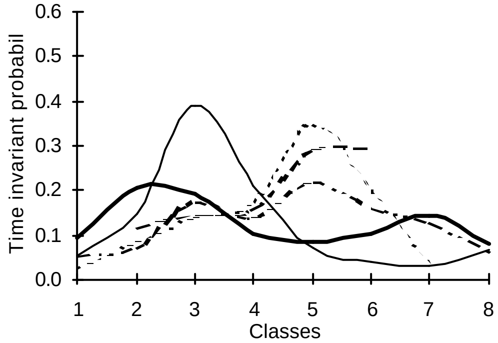


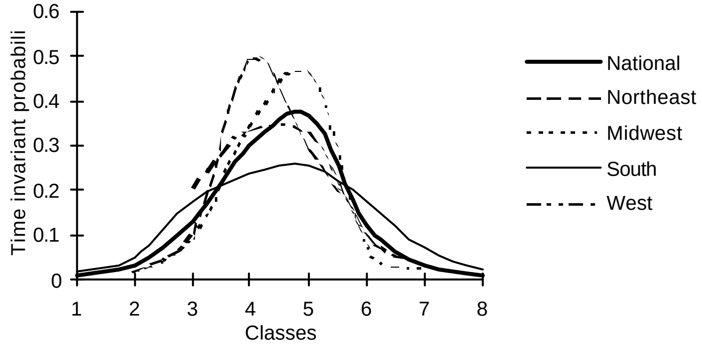
Figure 16. Productivity per farm in 1992 ('000 $)



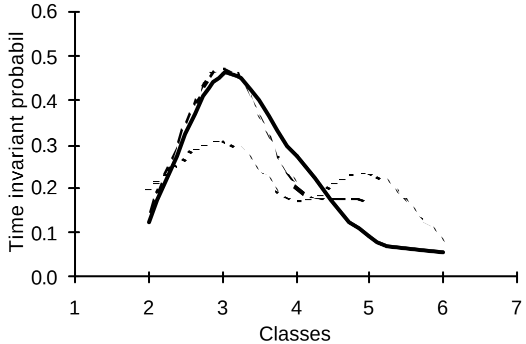
Figuur 17. Productivity per acre



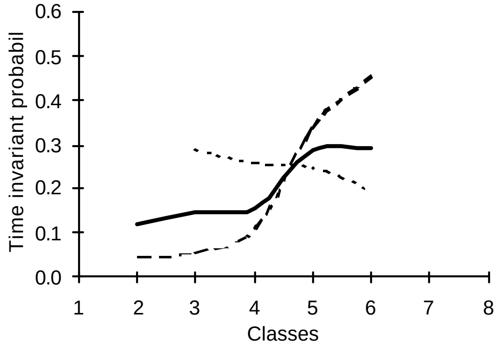
Figuur 18. Size per farm



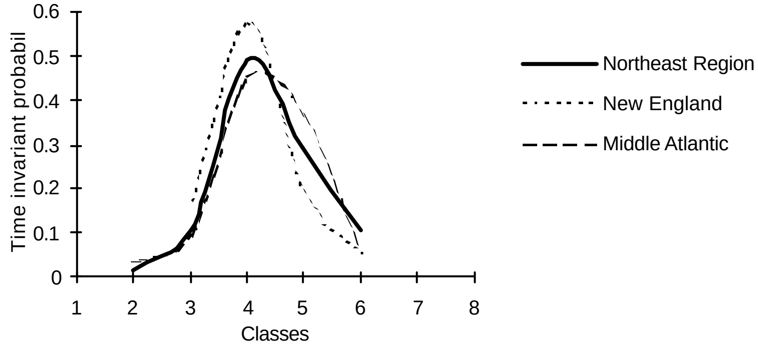
Figuur 19. Productivity per farm



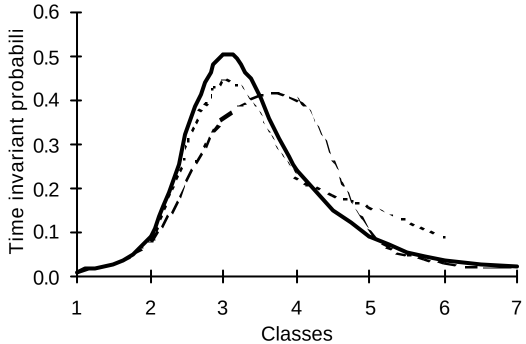
Figuur 20. Productivity per acre



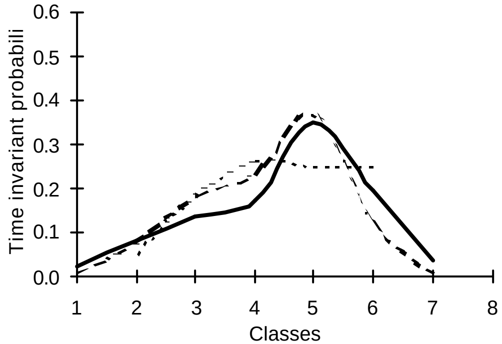
Figuur 21. Size per farm



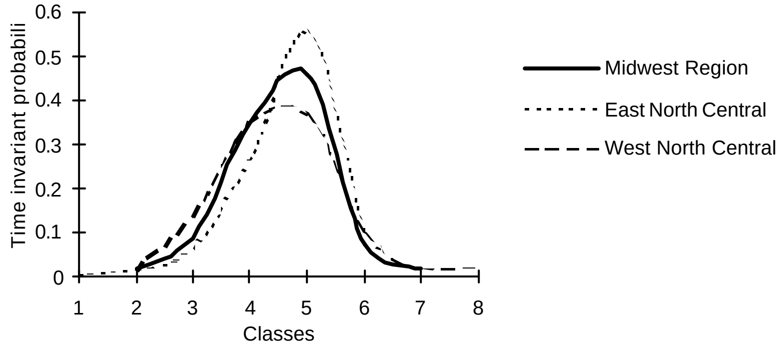
Figuur 22. Productivity per farm



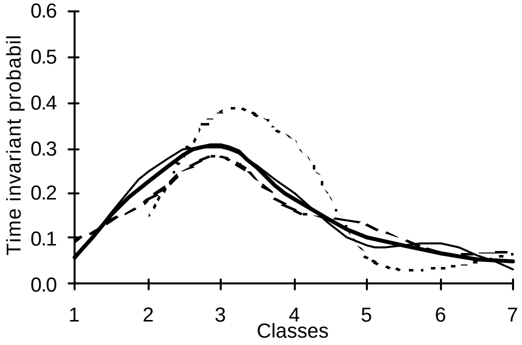
Figuur 23. Productivity per acre



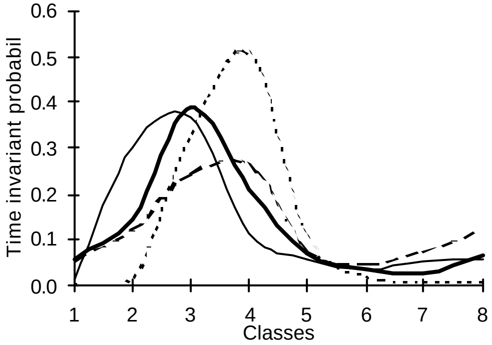
Figuur 24. Size per farm



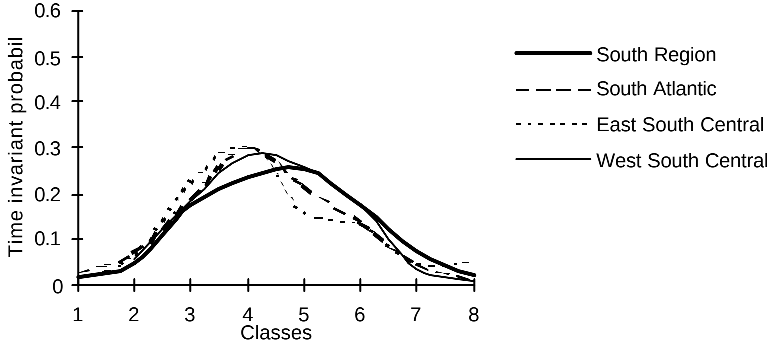
Figuur 25. Productivity per farm



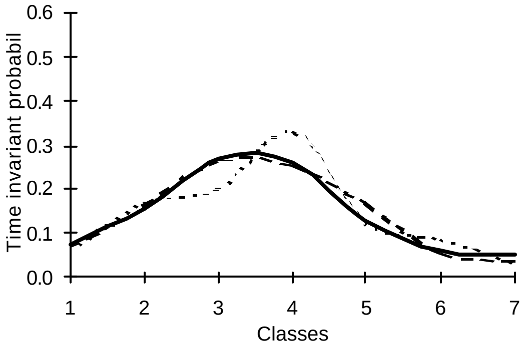
Figuur 26. Productivity per acre



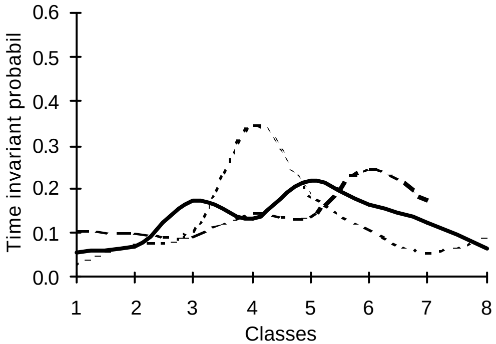
Figuur 27. Size per farm



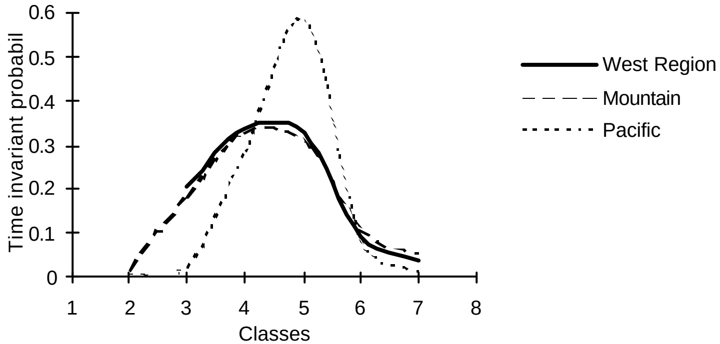
Figuur 28. Productivity per farm



Figuur 29. Productivity per acre



Figuur 30. Size per farm



Figuur 31. Productivity per farm

Table 1. Class definitions of productivity per acre and associate values of the original data.

Cut-off point	1	2	3	4	5	6
Year	0.850	0.925	1.000	1.075	1.150	1.225
1982	161	253	396	620	971	1521
1987	221	356	574	924	1487	2395
1992	289	476	784	1293	2131	3513

Table 2. Administrative regions and divisions

Region/Division	Obs.		Obs.
Northeast	201	West	363
New England	63	East North Central	430
Middle Atlantic	138	West North Central	615
South	1331	Midwest	1045
South Atlantic	529	Mountain	241
East South Central	362	Pacific	122
West South Central	440	National	2940

Table 3. Average productivity and size at national level

	Productivity per farm in constant 1990 US $	Size per farm in constant 1990 US $	Productivity per acre
1982	67,714	180	377
1987	94,932	171	554
1992	147,406	199	742

Table 4. Pearson correlation coefficient Productivity per Farm / Productivity per acre.

Region/Division	1982	1987	1992
National	-0.220	-0.106	-0.186
Northeast	-0.373	-0.273	-0.317
New England	-0.384	-0.377	-0.426
Middle Atlantic	-0.414	-0.310	-0.372
Midwest	-0.286	-0.216	-0.164
East North Central	-0.223	-0.227	-0.199
West North Central	-0.304	-0.223	-0.177
South	-0.192	-0.177	-0.137
South Atlantic	-0.208	-0.197	-0.209
East South Central	-0.286	-0.186	-0.188
West South Central	-0.212	-0.216	-0.146
West	-0.381	-0.119	-0.366
Mountain	-0.343	-0.327	-0.332
Pacific	-0.358	-0.121	-0.354

Size per Farm by Administrative Regions and Divisions: Transition Matrices

National

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 – 1.3	1.3 >	N
< .7	0.835	0.165							434
.7 – .8	0.072	0.792	0.136						682
.8 – .9	0.004	0.144	0.771	0.080	0.001				796
.9 – 1.0		0.005	0.137	0.773	0.084				934
1.0 – 1.1			0.002	0.107	0.777	0.112	0.001		970
1.1 – 1.2					0.082	0.801	0.117		1057
1.2 – 1.3					0.005	0.078	0.849	0.068	618
1.3 >					0.002		0.121	0.876	421
Time-invariant	0.095	0.208	0.187	0.105	0.083	0.102	0.142	0.078	5912
Iterations	12								
χ^2	70.835								
Eigenvalues	1.000	0.985	0.907	0.847	0.784	0.716	0.644	0.576	

North East Region

Classes	< .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 >	N
<. 8	0.890	0.110				27
.8 – .9	0.088	0.737	0.175			46
.9 – 1.0		0.152	0.685	0.164		92
1.0 – 1.1		0.006	0.083	0.815	0.096	157
1.1 >				0.093	0.907	86
Time-invariant	0.116	0.145	0.156	0.287	0.295	408
Iterations	10					
χ^2	6.851					
Eigenvalues	1.000	0.95	0.846	0.729	0.509	

New England

Classes	< .9	.9 – 1.0	1.0 – 1.1	1.1 >	N
< .9	0.919	0.081			25
.9 – 1.0	0.091	0.836	0.073		40
1.0 – 1.1		0.075	0.825	0.100	40
1.1 >			0.129	0.871	23
Time-invariant	0.291	0.259	0.253	0.197	128
Iterations	10				
χ^2	5.061				
Eigenvalues	1.000	0.949	0.804	0.698	

Middle Atlantic

Classes	< .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 >	N
<. 8	0.778	0.222				18
.8 – .9	0.153	0.676	0.170			19
.9 – 1.0	0.015	0.074	0.728	0.183		66
1.0 – 1.1			0.058	0.861	0.081	134
1.1 >				0.060	0.940	43
Time-invariant	0.046	0.056	0.107	0.337	0.455	280
Iterations	10					
χ^2	9.170					
Eigenvalues	1.000	0.946	0.855	0.681	0.500	

Mid West Region

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 >	N
< .7	0.833	0.167						20
.7 – .8	0.051	0.863	0.086					138
.8 – .9		0.053	0.872	0.075				281
.9 – 1.0			0.058	0.858	0.083			530
1.0 – 1.1				0.041	0.900	0.059		705
1.1 – 1.2					0.107	0.870	0.024	298
1.2 >						0.125	0.875	120
Time-invariant	0.026	0.084	0.136	0.174	0.350	0.193	0.036	2092
Iterations	11							
χ^2	44.299							
Eigenvalues	1.000	0.974	0.913	0.875	0.81	0.768	0.731	

East North Central

Classes	< .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 >	N
< .8	0.862	0.138				48
.8 – .9	0.039	0.882	0.079			103
.9 – 1.0		0.055	0.864	0.081		235
1.0 – 1.1			0.085	0.846	0.068	304
1.1 >				0.068	0.932	172
Time-invariant	0.052	0.185	0.263	0.249	0.251	862
Iterations	10					
χ^2	20.406					
Eigenvalues	1.000	0.959	0.888	0.801	0.738	

West North Central

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 >	N
< .7	0.579	0.421						19
.7 – .8	0.050	0.891	0.059					72
.8 – .9		0.025	0.909	0.066				122
.9 – 1.0			0.052	0.853	0.095			346
1.0 – 1.1				0.060	0.903	0.036		413
1.1 – 1.2					0.109	0.862	0.029	238
1.2 >						0.396	0.604	20
Time-invariant	0.009	0.077	0.183	0.233	0.367	0.123	0.009	1230
Iterations	10							
χ^2	27.828							
Eigenvalues	1.000	0.967	0.914	0.863	0.773	0.564	0.521	

South Region

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 – 1.3	1.3 >	N
< .7	0.782	0.209	0.009						193
.7 – .8	0.060	0.695	0.242	0.003					317
.8 – .9	0.006	0.079	0.786	0.125	0.002	0.002			498
.9 – 1.0	0.005	0.010	0.225	0.688	0.072				424
1.0 – 1.1			0.003	0.232	0.668	0.094	0.003		361
1.1 – 1.2				0.009	0.195	0.670	0.122	0.003	315
1.2 – 1.3					0.004	0.131	0.742	0.123	252
1.3 >						0.009	0.050	0.941	318
Time-invariant	0.055	0.146	0.389	0.210	0.069	0.036	0.030	0.065	2678
Iterations	11								
χ^2	78.639								
Eigenvalues	1.000	0.978	0.87	0.814	0.719	0.615	0.531	0.445	

South Atlantic

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 – 1.3	1.3 >	N
< .7	0.794	0.206							67
.7 – .8	0.052	0.666	0.283						119
.8 – .9	0.012	0.108	0.657	0.223					173
.9 – 1.0	0.005	0.015	0.180	0.711	0.089				209
1.0 – 1.1			0.020	0.273	0.567	0.140			150
1.1 – 1.2				0.006	0.230	0.575	0.189		148
1.2 – 1.3						0.121	0.626	0.253	115
1.3 >							0.146	0.854	89
Time-invariant	0.051	0.121	0.242	0.262	0.079	0.047	0.073	0.126	1070
Iterations	11								
χ^2	37.945								
Eigenvalues	1.000	0.977	0.846	0.754	0.645	0.515	0.409	0.304	

East South Central

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 – 1.3	1.3 >	N
< .7	0.790	0.210							70
.7 – .8	0.088	0.653	0.259						69
.8 – .9			0.784	0.216					122
.9 – 1.0		0.008	0.131	0.812	0.048				144
1.0 – 1.1			0.010	0.218	0.728	0.044			92
1.1 – 1.2				0.014	0.223	0.675	0.088		79
1.2 – 1.3				0.011		0.223	0.664	0.102	77
1.3 >						0.013	0.079	0.908	75
Time-invariant	0.006	0.015	0.331	0.507	0.106	0.019	0.007	0.008	728
Iterations	10								
χ^2	47.303								
Eigenvalues	0.999	0.949	0.87	0.826	0.708	0.583 + 0.022 I	0.583 - 0.022 I	0.495	

West South Central

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 – 1.3	1.3 >	N
< .7	0.625	0.375							48
.7 – .8	0.007	0.840	0.154						141
.8 – .9	0.007	0.120	0.798	0.069	0.007				135
.9 – 1.0			0.246	0.696	0.058				122
1.0 – 1.1				0.164	0.759	0.068	0.009		116
1.1 – 1.2					0.107	0.760	0.133		128
1.2 – 1.3					0.009	0.087	0.755	0.149	114
1.3 >							0.146	0.854	76
Time-invariant	0.012	0.306	0.370	0.113	0.055	0.035	0.053	0.055	880
Iterations	11								
χ^2	24.928								
Eigenvalues	1.001	0.983	0.869	0.781	0.69	0.61	0.599	0.555	

West Region

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 – 1.3	1.3 >	N
< .7	0.842	0.158							69
.7 – .8	0.121	0.753	0.126						84
.8 – .9		0.052	0.855	0.093					87
.9 – 1.0			0.117	0.776	0.095	0.012			85
1.0 – 1.1				0.066	0.838	0.089	0.006		167
1.1 – 1.2					0.130	0.791	0.079		115
1.2 – 1.3					0.011	0.090	0.809	0.091	99
1.3 >						0.023	0.166	0.811	42
Time-invariant	0.055	0.071	0.172	0.136	0.218	0.162	0.126	0.061	748
Iterations	11								
χ^2	24.423								
Eigenvalues	1.000	0.974	0.923	0.876	0.748	0.688	0.646	0.62	

Mountain

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 >	N
< .7	0.818	0.182						28
.7 – .8	0.194	0.722	0.083					36
.8 – .9		0.090	0.789	0.121				67
.9 – 1.0			0.076	0.800	0.123			89
1.0 – 1.1				0.131	0.767	0.103		120
1.1 – 1.2					0.057	0.818	0.125	88
1.2 >						0.182	0.818	60
Time-invariant	0.106	0.099	0.092	0.146	0.138	0.249	0.171	488
Iterations	11							
χ^2	8.564							
Eigenvalues	1.000	0.981	0.924	0.788	0.681	0.609	0.55	

Pacific

Classes	< .7	.7 – .8	.8 – .9	.9 – 1.0	1.0 – 1.1	1.1 – 1.2	1.2 – 1.3	1.3 >	N
< .7	0.818	0.182							18
.7 – .8	0.071	0.690	0.238						42
.8 – .9		0.174	0.739	0.087					46
.9 – 1.0			0.026	0.888	0.086				34
1.0 – 1.1				0.157	0.801	0.042			25
1.1 – 1.2					0.074	0.781	0.145		41
1.2 – 1.3						0.282	0.618	0.100	21
1.3 >							0.061	0.939	33
Time-invariant	0.030	0.077	0.105	0.346	0.189	0.107	0.055	0.091	260
Iterations	11								
χ^2	19.902								
Eigenvalues	1.000	0.977	0.947	0.887	0.796	0.713	0.485	0.469	

Productivity per Acre by Administrative Regions and Divisions: Transition Matrices

National

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.726	0.262	0.012					423
0.850 – 0.925	0.066	0.768	0.158	0.008				1197
0.925 – 1.000		0.166	0.707	0.123	0.005			1726
1.000 – 1.075			0.190	0.689	0.113	0.006	0.002	1268
1.075 – 1.150	0.002		0.008	0.272	0.554	0.148	0.015	566
1.150 – 1.225				0.017	0.222	0.593	0.168	347
1.225 >			0.003	0.003	0.017	0.157	0.820	337
Time-invariant	0.065	0.268	0.273	0.191	0.083	0.058	0.062	5864
Iterations	9							
χ^2	65.767							
Eigenvalues	1.000	0.938	0.828	0.693	0.583	0.479	0.316	

North East Region

Classes	< 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 >	N
< 0.925	0.746	0.240	0.014			71
0.925 – 1.000	0.070	0.827	0.092	0.011		173
1.000 – 1.075		0.159	0.728	0.113		88
1.075 – 1.150		0.062	0.333	0.517	0.088	33
1.150 >				0.151	0.849	33
Time-invariant	0.125	0.457	0.273	0.091	0.053	398
Iterations	8					
χ^2	10.552					
Eigenvalues	1.000	0.888	0.776	0.626	0.377	

New England

Classes	< 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 >	N
< 0.925	0.746	0.215	0.038			23
0.925 – 1.000	0.145	0.750	0.105			48
1.000 – 1.075	0.029	0.202	0.609	0.130	0.029	31
1.075 – 1.150			0.118	0.701	0.181	17
1.150 >				0.583	0.417	7
Time-invariant	0.198	0.310	0.174	0.236	0.082	126
Iterations	9					
χ^2	5.191					
Eigenvalues	1.000	0.918	0.625	0.481	0.199	

Middle Atlantic

Classes	< 0.925	0.925 – 1.000	1.000 – 1.075	> 1.075	N
< 0.925	0.881	0.119			25
0.925 – 1.000	0.037	0.896	0.060	0.007	134
1.000 – 1.075		0.154	0.768	0.078	78
1.075 >			0.113	0.887	35
Time-invariant	0.147	0.473	0.207	0.173	272
Iterations	9				
χ^2	5.490				
Eigenvalues	0.999	0.917	0.835	0.681	

Mid-West Region

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.721	0.279						115
0.850 – 0.925	0.029	0.702	0.264	0.005				206
0.925 – 1.000		0.048	0.859	0.088	0.003	0.001		712
1.000 – 1.075			0.192	0.745	0.063			727
1.075 – 1.150		0.004	0.004	0.177	0.748	0.067		265
1.150 – 1.225					0.159	0.745	0.096	44
1.225 >					0.045	0.091	0.864	21
Time-invariant	0.010	0.092	0.503	0.240	0.093	0.036	0.026	2090
Iterations	9							
χ^2	16.444							
Eigenvalues	0.999	0.936	0.828	0.771	0.686	0.606	0.559	

East North Central

Classes	< 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 >	N
< 0.925	0.780	0.220				60
0.925 – 1.000	0.032	0.895	0.071		0.002	431
1.000 – 1.075		0.128	0.785	0.080	0.007	298
1.075 – 1.150	0.021		0.111	0.827	0.042	55
1.150 >				0.100	0.900	16
Time-invariant	0.079	0.442	0.228	0.159	0.092	860
Iterations	9					
χ^2	30.418					
Eigenvalues	1.000	0.933	0.831	0.76	0.664	

West North Central

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.683	0.317						93
0.850 – 0.925	0.026	0.759	0.215					159
0.925 – 1.000		0.050	0.834	0.108	0.009			344
1.000 – 1.075			0.102	0.833	0.062	0.002		401
1.075 – 1.150				0.283	0.630	0.081	0.005	171
1.150 – 1.225				0.024	0.268	0.561	0.148	41
1.225 >						0.236	0.764	21
Time-invariant	0.007	0.082	0.353	0.402	0.100	0.033	0.023	1230
Iterations	9							
χ^2	10.849							
Eigenvalues	1.105	0.874	0.727 + 0.193 I	0.727 - 0.193 I	0.712	0.6	0.319	

South Region

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.565	0.421	0.014					189
0.850 – 0.925	0.113	0.696	0.172	0.019				577
0.925 – 1.000	0.002	0.137	0.671	0.180	0.007	0.001	0.001	752
1.000 – 1.075		0.008	0.307	0.548	0.127	0.011		532
1.075 – 1.150			0.021	0.239	0.560	0.166	0.014	279
1.150 – 1.225			0.017	0.007	0.267	0.599	0.110	173
1.225 >					0.026	0.171	0.803	152
Time-invariant	0.060	0.226	0.306	0.187	0.103	0.069	0.048	2654
Iterations	9							
χ^2	75.688							
Eigenvalues	1.000	0.916	0.794	0.668	0.447	0.367	0.250	

South Atlantic

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.740	0.260						77
0.850 – 0.925	0.111	0.663	0.209	0.014	0.005			216
0.925 – 1.000	0.007	0.138	0.694	0.155	0.003	0.003		308
1.000 – 1.075		0.010	0.270	0.543	0.167	0.010		196
1.075 – 1.150			0.015	0.221	0.594	0.163	0.007	137
1.150 – 1.225				0.014	0.329	0.454	0.204	55
1.225 >						0.213	0.787	61
Time-invariant	0.087	0.187	0.281	0.166	0.132	0.073	0.074	1050
Iterations	9							
χ^2	38.152							
Eigenvalues	1.000	0.929	0.815	0.687	0.496	0.354	0.193	

East South Central

Classes	< 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.925	0.731	0.258	0.012				174
0.925 – 1.000	0.102	0.711	0.187				211
1.000 – 1.075	0.004	0.225	0.670	0.095	0.005		213
1.075 – 1.150		0.019	0.429	0.413	0.130	0.010	75
1.150 – 1.225				0.150	0.650	0.200	25
1.225 >			0.033	0.045	0.033	0.888	26
Time-invariant	0.148	0.377	0.309	0.064	0.035	0.067	724
Iterations	9						
χ^2	55.249						
Eigenvalues	1.000	0.922	0.752	0.652	0.492	0.246	

West South Central

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.420	0.552	0.028					74
0.850 – 0.925	0.123	0.691	0.173	0.014				220
0.925 – 1.000		0.156	0.699	0.141			0.004	207
1.000 – 1.075			0.233	0.650	0.111	0.006		172
1.075 – 1.150				0.274	0.545	0.157	0.024	83
1.150 – 1.225			0.014		0.187	0.720	0.080	56
1.225 >					0.012	0.306	0.682	68
Time-invariant	0.052	0.245	0.302	0.197	0.085	0.087	0.032	880
Iterations	9							
χ^2	20.739							
Eigenvalues	1.000	0.922	0.78	0.614	0.511	0.337	0.243	

West Region

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.803	0.197						121
0.850 – 0.925	0.093	0.682	0.203	0.022				137
0.925 – 1.000		0.120	0.721	0.147	0.012			150
1.000 – 1.075		0.011	0.153	0.749	0.078	0.009		101
1.075 – 1.150			0.021	0.172	0.710	0.087	0.010	101
1.150 – 1.225			0.014		0.235	0.626	0.125	65
1.225 >						0.175	0.825	61
Time-invariant	0.074	0.156	0.269	0.260	0.130	0.060	0.051	736
Iterations	9							
χ^2	43.698							
Eigenvalues	1.000	0.931	0.861	0.746	0.626	0.488	0.463	

Mountains

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.790	0.210						55
0.850 – 0.925	0.073	0.625	0.271	0.031				96
0.925 – 1.000	0.008	0.176	0.649	0.159	0.009			119
1.000 – 1.075			0.194	0.637	0.170			86
1.075 – 1.150				0.258	0.625	0.098	0.019	50
1.150 – 1.225				0.045	0.315	0.530	0.110	45
1.225 >						0.256	0.744	31
Time-invariant	0.066	0.160	0.264	0.254	0.167	0.054	0.036	482
Iterations	9							
χ^2	13.594							
Eigenvalues	1.001	0.903	0.809	0.707	0.512	0.378	0.291	

Pacific

Classes	< 0.850	0.850 – 0.925	0.925 – 1.000	1.000 – 1.075	1.075 – 1.150	1.150 – 1.225	1.225 >	N
< 0.850	0.807	0.193						41
0.850 – 0.925	0.067	0.787	0.146					39
0.925 – 1.000		0.104	0.722	0.174				42
1.000 – 1.075			0.095	0.810	0.078	0.017		62
1.075 – 1.150		0.028		0.230	0.586	0.157		29
1.150 – 1.225					0.283	0.587	0.129	24
1.225 >						0.340	0.660	17
Time-invariant	0.058	0.167	0.201	0.331	0.122	0.088	0.033	254
Iterations	9							
χ^2	25.135							
Eigenvalues	1.000	0.927	0.851	0.731	0.617	0.536	0.298	

Productivity per Farm by Administrative Regions and Divisions: Transition Matrices

National

Classes	< .675	0.675 – 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	1.250 – 1.375	1.375 >	N
< 0.675	0.748	0.235	0.010	0.007					282
0.675 – 0.750	0.041	0.670	0.265	0.022	0.002				420
0.750 – 0.875	0.005	0.073	0.676	0.239	0.008				792
0.875 – 1.000			0.105	0.737	0.153	0.004			1365
1.000 – 1.125			0.004	0.128	0.780	0.087	0.002		1639
1.125 – 1.250				0.003	0.274	0.645	0.077		1006
1.250 – 1.375					0.003	0.302	0.641	0.054	314
1.375 >					0.004	0.017	0.183	0.795	230
Time-invariant	0.008	0.035	0.130	0.299	0.365	0.122	0.033	0.009	6048
Iterations	9								
χ^2	49.583								
Eigenvalues	1.000	0.895	0.842	0.771	0.68	0.604	0.472	0.428	

North East Region

Classes	< 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	> 1.125	N
< 0.750	0.619	0.310		0.071		13
0.750 – 0.875	0.054	0.637	0.287	0.022		51
0.875 – 1.000		0.060	0.847	0.093		138
1.000 – 1.125		0.014	0.156	0.757	0.073	148
1.125 >				0.206	0.794	58
Time-invariant	0.015	0.104	0.490	0.289	0.103	408
Iterations	8					
χ^2	8.498					
Eigenvalues	1.000	0.851	0.714	0.616	0.473	

New England

Classes	< 0.875	0.875 – 1.000	1.000 – 1.125	> 1.125	N
< 0.875	0.690	0.310			13
0.875 – 1.000	0.077	0.831	0.092		54
1.000 – 1.125	0.033	0.386	0.472	0.109	38
1.125 >			0.331	0.669	23
Time-invariant	0.175	0.639	0.140	0.046	128
Iterations	7				
χ^2	9.282				
Eigenvalues	1.000	0.789	0.61	0.45	

Middle Atlantic

Classes	< 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 >	N
< 0.750	0.686	0.243		0.071		12
0.750 – 0.875	0.065	0.636	0.268	0.031		39
0.875 – 1.000		0.048	0.858	0.094		84
1.000 – 1.125		0.009	0.082	0.854	0.055	110
1.125 >				0.113	0.887	35
Time-invariant	0.013	0.064	0.344	0.389	0.189	280
Iterations	9					
χ^2	9.734					
Eigenvalues	1.000	0.876	0.789	0.756	0.513	

Mid-West Region

Classes	< 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	> 1.250	N
< 0.750	0.798	0.193	0.009				128
0.750 – 0.875	0.035	0.771	0.191	0.004			231
0.875 – 1.000		0.051	0.833	0.115			624
1.000 – 1.125			0.088	0.861	0.049	0.001	774
1.125 – 1.250				0.331	0.624	0.044	270
1.250 >					0.202	0.798	73
Time-invariant	0.015	0.090	0.346	0.459	0.070	0.019	2100
Iterations	9						
χ^2	24.056						
Eigenvalues	0.999	0.891	0.828	0.774	0.658	0.535	

East North Central

Classes	< .675	0.675 – 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	> 1.125	N
< 0.675	0.582	0.418					29
0.675 – 0.750	0.066	0.670	0.247	0.017			61
0.750 – 0.875	0.008	0.034	0.771	0.178	0.008		118
0.875 – 1.000			0.030	0.859	0.110		298
1.000 – 1.125				0.088	0.874	0.038	302
1.125 >					0.487	0.513	58
Time-invariant	0.003	0.010	0.063	0.391	0.495	0.039	866
Iterations	9						
χ^2	17.878						
Eigenvalues	1.000	0.913	0.805	0.684	0.646	0.336	

West North Central

Classes	< 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	1.250 – 1.375	1.375 >	N
< 0.750	0.759	0.241						38
0.750 – 0.875	0.026	0.770	0.204					113
0.875 – 1.000		0.070	0.810	0.120				326
1.000 – 1.125			0.088	0.853	0.057	0.002		472
1.125 – 1.250				0.288	0.656	0.056		212
1.250 – 1.375					0.317	0.567	0.115	43
1.375 >					0.033	0.167	0.800	30
Time-invariant	0.012	0.110	0.321	0.439	0.090	0.018	0.010	1234
Iterations	9							
χ^2	19.956							
Eigenvalues	1.000	0.941	0.882	0.793	0.722	0.649	0.500	

South Region

Classes	< .675	0.675 – 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	1.250 – 1.375	1.375 >	N
< 0.675	0.758	0.223	0.014	0.005					203
0.675 – 0.750	0.064	0.638	0.285	0.009	0.004				235
0.750 – 0.875	0.005	0.077	0.710	0.204	0.005				408
0.875 – 1.000		0.004	0.149	0.661	0.175	0.011			537
1.000 – 1.125			0.004	0.171	0.667	0.147	0.011		530
1.125 – 1.250				0.002	0.229	0.644	0.121	0.002	392
1.250 – 1.375				0.004	0.033	0.302	0.599	0.061	241
1.375 >						0.005	0.214	0.781	188
Time-invariant	0.017	0.050	0.175	0.237	0.254	0.173	0.071	0.022	2734
Iterations	9								
χ^2	37.401								
Eigenvalues	1.000	0.913	0.83	0.769	0.649	0.526	0.428	0.344	

South Atlantic

Classes	< .675	0.675 – 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	1.250 – 1.375	1.375 >	N
< 0.675	0.813	0.158	0.020	0.009					100
0.675 – 0.750	0.034	0.671	0.273	0.011	0.011				88
0.750 – 0.875	0.015	0.055	0.617	0.306	0.007				130
0.875 – 1.000		0.011	0.166	0.649	0.169	0.005			188
1.000 – 1.125			0.005	0.155	0.655	0.175	0.010		206
1.125 – 1.250					0.206	0.661	0.132		189
1.250 – 1.375					0.043	0.264	0.633	0.061	115
1.375 >							0.200	0.800	60
Time-invariant	0.017	0.037	0.128	0.225	0.253	0.211	0.099	0.030	1076
Iterations	9								
χ^2	23.704								
Eigenvalues	1.000	0.913	0.837	0.783	0.666	0.558	0.398	0.323	

East South Central

Classes	< .675	0.675 – 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	1.250 – 1.375	1.375 >	N
< 0.675	0.753	0.236	0.010						94
0.675 – 0.750	0.064	0.682	0.254						110
0.750 – 0.875		0.098	0.790	0.113					177
0.875 – 1.000			0.142	0.658	0.193	0.007			146
1.000 – 1.125				0.157	0.685	0.141	0.017		113
1.125 – 1.250				0.020	0.270	0.620	0.090		45
1.250 – 1.375				0.038		0.329	0.549	0.084	24
1.375 >							0.196	0.804	15
Time-invariant	0.025	0.097	0.256	0.203	0.232	0.126	0.042	0.018	724
Iterations	9								
χ^2	25.927								
Eigenvalues	1.000	0.938	0.843	0.783	0.642	0.504	0.439	0.186	

West South Central

Classes	< 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	1.250 – 1.375	1.375 >	N
< 0.750	0.652	0.329	0.019					46
0.750 – 0.875	0.069	0.691	0.230	0.010				101
0.875 – 1.000		0.138	0.675	0.167	0.020			203
1.000 – 1.125		0.005	0.194	0.670	0.122	0.009		211
1.125 – 1.250				0.243	0.635	0.117	0.006	158
1.250 – 1.375				0.029	0.335	0.579	0.057	102
1.375 >					0.009	0.222	0.769	113
Time-invariant	0.033	0.166	0.283	0.274	0.163	0.062	0.019	934
Iterations	9							
χ^2	40.842							
Eigenvalues	0.999	0.89	0.781	0.699	0.596	0.501	0.358	

West Region

Classes	< 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	> 1.250	N
< 0.875	0.826	0.168	0.006			172
0.875 – 1.000	0.107	0.743	0.151			226
1.000 – 1.125	0.005	0.168	0.753	0.074		228
1.125 – 1.250		0.009	0.241	0.676	0.074	126
1.250 >		0.018		0.163	0.819	54
Time-invariant	0.222	0.350	0.305	0.088	0.036	806
Iterations	9					
χ^2	16.604					
Eigenvalues	1.000	0.891	0.8	0.628	0.502	

Mountain

Classes	< 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	> 1.250	N
< 0.750	0.722	0.239	0.038				36
0.750 – 0.875	0.026	0.756	0.208	0.010			82
0.875 – 1.000		0.129	0.736	0.135			163
1.000 – 1.125		0.006	0.199	0.701	0.094		160
1.125 – 1.250			0.016	0.284	0.602	0.099	73
1.250 >					0.192	0.808	30
Time-invariant	0.021	0.227	0.377	0.254	0.080	0.041	544
Iterations	9						
χ^2	24.551						
Eigenvalues	1.000	0.893	0.786	0.688	0.565	0.417	

Pacific

Classes	< 0.750	0.750 – 0.875	0.875 – 1.000	1.000 – 1.125	1.125 – 1.250	> 1.250	N
< 0.750	0.776	0.224					26
0.750 – 0.875	0.077	0.574	0.349				28
0.875 – 1.000		0.047	0.761	0.192			63
1.000 – 1.125			0.095	0.880	0.026		68
1.125 – 1.250				0.182	0.780	0.038	53
1.250 >			0.042		0.125	0.833	24
Time-invariant	0.013	0.038	0.284	0.570	0.076	0.018	262
Iterations	8						
χ^2	10.084						
Eigenvalues	1.000	0.878	0.843	0.744	0.68	0.473	